Problem Set 6

Prasanna Parasurama
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I. PROBLEM 1

This exercise asks you to implement and assess the performance of the bootstrap for the linear regression model. Suppose you have the linear regression model:

$$y_i = \beta_0 + \beta_1 x_i + \epsilon_i$$

where,

- $x_i \sim U[0, 2]$
- $\epsilon_i | x_i \sim U[-1, 1]$
- $\beta_0 = \beta_1 = 1$

We ask you to answer the following questions:

a. Write a code that generates i.i.d. samples of sizes $n = 10, 50, 200$ from that distribution, computes (1) the least squares estimator for β, (2) the t-ratio for the least squares coefficient β_1, $t_n = \frac{\hat{\beta}_{1,LS}-1}{\hat{s.e.}(\hat{\beta}_{1,LS})}$, and (3) the least square residuals $\hat{\epsilon}_i = y_i - \hat{\beta}_{0,LS} - \hat{\beta}_{1,LS} x_i$

```
In [1]: import numpy as np
        import pandas as pd
        import statsmodels.api as sm
        import matplotlib.pyplot as plt
        from datetime import datetime
        %matplotlib inline
```

```
In [2]: class BootstrapSimulator:
            def __init__(self, n):
                self.n = n  # sample size

                self.df = pd.DataFrame()

                self.ols = None
                self.b0_ols = None
                self.b1_ols = None
                self.t_ols = None

            def draw_samples(self):
                n = self.n

                self.df['x'] = np.random.uniform(0, 2, n)
                self.df['e'] = np.random.uniform(-1, 1, n)
                self.df['y'] = 1 + self.df['x'] + self.df['e']
                self.df['intercept'] = np.ones(n)
                return self.df

            @staticmethod
            def get_ols_params(fitted_model):
```

```
        b_hat = fitted_model.params['x']
        b_se = fitted_model.bse['x']
        t = (b_hat - 1) / b_se
        return b_hat, t

    def fit_ols(self, y="y"):
        # fit model
        self.ols = sm.OLS(self.df[y], self.df[['x', 'intercept']]).fit()

        self.b1_ols, self.t_ols = self.get_ols_params(self.ols)
        self.b0_ols = self.ols.params['intercept']

        # residuals
        self.df['e_hat'] = self.df[y] - self.b0_ols - self.b1_ols * self.df['x']

        return self.b1_ols, self.t_ols

    def sample_residuals(self):
        n = len(self.df)
        return np.random.choice(self.df['e_hat'], n, replace=True)

    @staticmethod
    def get_bootstrap_stats(params):
        return {'ci': (np.percentile(params, 2.5), np.percentile(params, 97.5)),
                'mean': np.mean(params)}

    def residual_bootstrap(self, n_reps=200):

        b_bootstrap = list()
        t_bootstrap = list()

        stats = dict()

        for _ in range(n_reps):
            e_bootstrap = self.sample_residuals()
            self.df['y_bootstrap'] = self.b0_ols + self.b1_ols * self.df['x'] +
e_bootstrap
            ols = sm.OLS(self.df["y_bootstrap"], self.df[['x', 'intercept']]).fit()
            b, t = self.get_ols_params(ols)
            b_bootstrap.append(b)
            t_bootstrap.append(t)

        stats['b'] = self.get_bootstrap_stats(b_bootstrap)
        stats['t'] = self.get_bootstrap_stats(t_bootstrap)

        return stats

    def parametric_bootstrap(self, n_reps=200):
        b_bootstrap = list()
        t_bootstrap = list()

        stats = dict()

        for _ in range(n_reps):
            self.df['e'] = np.random.uniform(-1, 1, self.n)
            self.df['y'] = self.b0_ols + self.b1_ols * self.df['x'] + self.df['e']
```

```
                ols = sm.OLS(self.df['y'], self.df[['x', 'intercept']]).fit()

                b, t = self.get_ols_params(ols)
                b_bootstrap.append(b)
                t_bootstrap.append(t)
            stats['b'] = self.get_bootstrap_stats(b_bootstrap)
            stats['t'] = self.get_bootstrap_stats(t_bootstrap)

            return stats
```

See `draw_samples` and `fit_ols` methods.

b. Write a code for drawing n times at random from the discrete uniform distribution over the estimated residuals $\hat{\epsilon}_1, ..., \hat{\epsilon}_n$ (i.e. with replacement).

See `sample_residuals` method in `BootstrapSimulator` class.

c. Use your code from parts (a) and (b) to implement the residual bootstrap - assuming that ϵ_i and x_i are independent - to estimate the 95th percentiles of the respective distributions of $\hat{\beta}_{1,LS}$ and t_n

```
In [3]: bs_10 = BootstrapSimulator(n=10)
        bs_50 = BootstrapSimulator(n=50)
        bs_200 = BootstrapSimulator(n=200)

        bs_10.draw_samples()
        bs_10.fit_ols()

        bs_50.draw_samples()
        bs_50.fit_ols()

        bs_200.draw_samples()
        bs_200.fit_ols()

Out[3]: (0.9850883905439032, -0.19459470136382742)
```

```
In [4]: # Residual bootstrap
        res_10 = bs_10.residual_bootstrap()
        res_50 = bs_50.residual_bootstrap()
        res_200 = bs_200.residual_bootstrap()
```

```
In [5]: df_res = pd.DataFrame([res_10, res_50, res_200])

        print('b estimates')
        print(df_res['b'].apply(pd.Series))

        print('t estimates')
        print(df_res['t'].apply(pd.Series))
```

```
b estimates
                                          ci      mean
0  (0.1252409779586813, 0.8744245281189442)  0.497854
1  (0.7564703092768035, 1.3095184865086547)  1.024620
2  (0.8415242880163574, 1.1121380817466304)  0.975943
t estimates
                                            ci      mean
0  (-4.9693357957442394, -0.5040697930336879) -2.357089
1    (-1.8305105346400985, 2.240661045221299)  0.177186
2     (-2.016877673129661, 1.467179807545017) -0.316971
```

d. Repeat part (a) for sample size $n = 10, 50, 200$ with 200 replications, where you keep the initial draws of $x_1, .., x_n$ from part (a) and only generate new residuals from their conditional distribution. Compute $\hat{\beta}_{1,LS}$ and the statistic t_n using 200 independent samples of size n. Use your results to compute a simulated estimate for the 95th percentiles of the respective sampling distributions for $\hat{\beta}_{1,LS}$ and t_n.

```
In [6]: # parametric bootstrap
        par_10 = bs_10.parametric_bootstrap()
        par_50 = bs_50.parametric_bootstrap()
        par_200 = bs_200.parametric_bootstrap()
```

```
In [7]: df_par = pd.DataFrame([par_10, par_50, par_200])

        print('b estimates')
        print(df_par['b'].apply(pd.Series))

        print('t estimates')
        print(df_par['t'].apply(pd.Series))
```

```
b estimates
                                              ci      mean
0  (-0.07770851234812026, 1.0908798535407562)  0.481773
1    (0.7336699250353068, 1.2440893219167681)  1.014423
2    (0.8299080953533149, 1.1223787253665154)  0.985627
t estimates
                                             ci      mean
0   (-4.249443952035807, 0.3108292477213074) -1.776718
1  (-2.0759239890186234, 1.7110379456127023)  0.091293
2  (-2.3983362460727142, 1.6721542243509722) -0.196839
```

e. Compare your results from (c) and (d). What do you conclude about the performance of the bootstrap? How does it compare to the 95th percentile of the asymptotic distribution of t_n?

Both residual (c) and parametric (d) bootstrap give similar results for *beta* estimates. For t estimates, they are different for n=2, but tend to converge for higher n.

```
In [8]: def get_asymptotic_ci(bs_sim, stat):
            if stat == "b":
                return (bs_sim.ols.params['x'] - 2*bs_sim.ols.bse['x'], bs_sim.ols.params['x'] +
        2*bs_sim.ols.bse['x'])
            elif stat == "t":
                return (((bs_sim.ols.params['x'] - 2*bs_sim.ols.bse['x']) -
        1)/bs_sim.ols.bse['x'], ((bs_sim.ols.params['x'] + 2*bs_sim.ols.bse['x']) -
        1)/bs_sim.ols.bse['x'])
```

For, $\hat{\beta}_1$, note that the bootstrap CI are fairly close to asymptotic distribution CI:

```
In [9]: print(get_asymptotic_ci(bs_10, stat="b"))
        print(get_asymptotic_ci(bs_50, stat="b"))
        print(get_asymptotic_ci(bs_200, stat="b"))
```

```
(0.0012296909768160225, 1.0016978646647163)
(0.7340372030038689, 1.3007819814839865)
(0.831830266334066, 1.1383465147537404)
```

To get asymptotic distribution of t_n, we would have to rely on the delta method. But since β_1 and $se(beta_1)$ are independent, we can do a simple substitution. The bootstrap estimates converge for larger n.

```
In [10]: print(get_asymptotic_ci(bs_10, stat="t"))
         print(get_asymptotic_ci(bs_50, stat="t"))
         print(get_asymptotic_ci(bs_200, stat="t"))
```

```
(-3.9932117194354806, 0.006788280564518 93)
(-1.877125698162645, 2.122874301837354)
(-2.1945947013638274, 1.8054052986361726)
```

II. PROBLEM 2

This exercise will walk you through a prediction task. I have downloaded data from a peer-to-peer lending platform, Lending Club. The dataset you will work with is: **lending_club_07_to_11_cleaned.csv**. Lending Club provides detailed characteristic information regarding loans, both information on the borrower, as well as, the loan itself. Your goal will be to build a model to predict the outcome of a loan, i.e. whether an individual paid off a loan or did not pay off a loan. In our case, a good outcome is if the loan is fully paid off, a bad outcome is if the loan is charged off.

The target variable for the analysis is **loan_status**, where:

$$loan\_status = \begin{cases} 1 \text{ if loan is paid off} \\ 0 \text{ if loan is not paid off} \end{cases}$$

```
In [11]: import pandas as pd

         df = pd.read_csv("data/lending_club_07_to_11_cleaned.csv")
```

a. This is going to be a more DIY style exercise, provide a list of the variables you plan to use for the analysis. Give a short discussion for why you excluded other variables.

```
In [12]: vars_to_include = ["addr_state",
                            "annual_inc",
                            "delinq_2yrs",
                            "dti",
                            "emp_length",
                            "funded_amnt",
                            "home_ownership",
                            "inq_last_6mths",
                            "installment",
                            "int_rate",
                            'loan_amnt',
                            'open_acc',
                            'pub_rec',
                            'pub_rec_bankruptcies',
                            'purpose',
                            'revol_bal',
                            'revol_util',
                            'sub_grade',
                            'term',
                            'total_acc',
                            'total_pymnt',
                            'total_rec_int',
                            'total_rec_late_fee',
                            'total_rec_prncp',
                            'verification_status',
                            'zip_code']
```

In [13]:
```
# convert to datetime
df['issue_d'] = pd.to_datetime(df['issue_d'], format='%b-%y')
df['earliest_cr_line'] = pd.to_datetime(df['earliest_cr_line'], format='%b-%y')
df['last_pymnt_d'] = pd.to_datetime(df['last_pymnt_d'], format='%b-%y')
df['last_credit_pull_d'] = pd.to_datetime(df['last_credit_pull_d'], format='%b-%y')
```

In [14]:
```
# create new features
df['days_since_first_cr_line'] = (df['issue_d'] - df['earliest_cr_line']).apply(lambda
x: x.days)
df['days_since_last_pymnt'] = (datetime.today() - df['last_pymnt_d']).apply(lambda x:
x.days)
df['days_since_last_cr_pull'] = (datetime.today() -
df['last_credit_pull_d']).apply(lambda x: x.days)
```

In [15]:
```
vars_to_include.extend(['days_since_first_cr_line', 'days_since_last_pymnt',
'days_since_last_cr_pull'])
```

In [16]:
```
df[vars_to_include].dtypes
```

Out[16]:
```
addr_state                    object
annual_inc                   float64
delinq_2yrs                    int64
dti                          float64
emp_length                    object
funded_amnt                    int64
home_ownership                object
inq_last_6mths                 int64
installment                  float64
int_rate                      object
loan_amnt                      int64
open_acc                       int64
pub_rec                        int64
pub_rec_bankruptcies         float64
purpose                       object
revol_bal                      int64
revol_util                    object
sub_grade                     object
term                          object
total_acc                      int64
total_pymnt                  float64
total_rec_int                float64
total_rec_late_fee           float64
total_rec_prncp              float64
verification_status           object
zip_code                      object
days_since_first_cr_line       int64
days_since_last_pymnt        float64
days_since_last_cr_pull      float64
dtype: object
```

In [17]:
```
# convert to proper data types
df['int_rate'] = df['int_rate'].apply(lambda x: float(x[:-1]) if x is not np.nan else x)
df['revol_util'] = df['revol_util'].apply(lambda x: float(x[:-1]) if x is not np.nan
else x)
```

The following variables are ommitted, because there is no variance in the data: `acc_now_delinq`, `chargeoff_within_12_mths`, `collections_12_mths_ex_med`, `delinq_amnt`, `disbursement method`, hardship_flag, initial_list_status, out_prncp, out_prncp_inv, policy_code, pymnt_plan, tax_liens.

The following variables are omitted because it is not in the data dictionary, and I can't infer what they mean: collection_recovery_fee, debt_settlement_flag, funded_amnt_inv, total_pymnt_inv, recoveries.

grade is fully capture in sub_grade.

Instead of including, issue_d, earliest_cr_line, last_credit_pull_d, last_pymnt_d, I included 3 transformed features: days_since_first_cr_line, days_since_last_pymnt, days_since_last_pymnt

b. Regularization is an important step when using an machine learning algorithm, regularzie the variables that you have included. Briefly, why is regularization important?

Regularization centers and scales the data. It helps with gradient descent convergence as the gradient surface won't be skewed in any particular dimension

```
In [18]: data = df[vars_to_include+['loan_status']]
         data = data.dropna().reset_index(drop=True)

         X = data[vars_to_include]
```

```
In [19]: from sklearn.preprocessing import StandardScaler

         data = df[vars_to_include+['loan_status']]
         data = data.dropna().reset_index(drop=True)

         X = data[vars_to_include]
         y = data['loan_status']
         # get numeric column types

         numeric_cols = [k for k,v in X.dtypes.to_dict().items() if v in [int, float]]
         print(numeric_cols)
         scaler = StandardScaler()

         X[numeric_cols] = scaler.fit_transform(X[numeric_cols])
```

```
['annual_inc', 'delinq_2yrs', 'dti', 'funded_amnt', 'inq_last_6mths', 'installment',
'int_rate', 'loan_amnt', 'open_acc', 'pub_rec', 'pub_rec_bankruptcies', 'revol_bal',
'revol_util', 'total_acc', 'total_pymnt', 'total_rec_int', 'total_rec_late_fee',
'total_rec_prncp', 'days_since_first_cr_line', 'days_since_last_pymnt',
'days_since_last_cr_pull']


/Users/parasu/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:14:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy

/Users/parasu/anaconda3/lib/python3.6/site-packages/pandas/core/indexing.py:543:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy
  self.obj[item] = s
```

c. Provide a simple correlational table to give you a sense of the relationship between your covariates. Do you notice any interesting patterns?

In [20]:
```
import seaborn as sns

cor_table = X[numeric_cols].corr()

cor_table
```

Out[20]:
```
                        annual_inc  delinq_2yrs       dti  funded_amnt  \
annual_inc                1.000000     0.022445 -0.124681     0.268287
delinq_2yrs               0.022445     1.000000 -0.036118    -0.034389
dti                      -0.124681    -0.036118  1.000000     0.065301
funded_amnt               0.268287    -0.034389  0.065301     1.000000
inq_last_6mths            0.033472     0.007069 -0.000236     0.007624
installment               0.272153    -0.022195  0.053239     0.955391
int_rate                  0.052448     0.158380  0.108273     0.313052
loan_amnt                 0.272296    -0.033730  0.065034     0.981301
open_acc                  0.157171     0.011986  0.290514     0.172354
pub_rec                  -0.015147     0.009970 -0.005554    -0.048898
pub_rec_bankruptcies     -0.012931     0.004945  0.005774    -0.034133
revol_bal                 0.279054    -0.056674  0.228631     0.313264
revol_util                0.017173    -0.044628  0.276073     0.069696
total_acc                 0.237203     0.068196  0.229083     0.249831
total_pymnt               0.257571    -0.023685  0.064530     0.903647
total_rec_int             0.185332     0.022342  0.104411     0.736995
total_rec_late_fee        0.008124     0.033372 -0.010295     0.052480
total_rec_prncp           0.259872    -0.039953  0.041901     0.874004
days_since_first_cr_line  0.180313     0.064830  0.050192     0.193477
days_since_last_pymnt    -0.015844     0.005000 -0.097698    -0.146958
days_since_last_cr_pull   0.010625    -0.007269 -0.119076    -0.042719

                        inq_last_6mths  installment  int_rate  loan_amnt  \
annual_inc                    0.033472     0.272153  0.052448   0.272296
delinq_2yrs                   0.007069    -0.022195  0.158380  -0.033730
dti                          -0.000236     0.053239  0.108273   0.065034
funded_amnt                   0.007624     0.955391  0.313052   0.981301
inq_last_6mths                1.000000     0.007526  0.134738   0.007576
installment                   0.007526     1.000000  0.282471   0.929132
int_rate                      0.134738     0.282471  1.000000   0.309604
loan_amnt                     0.007576     0.929132  0.309604   1.000000
open_acc                      0.092757     0.169679  0.013577   0.173914
pub_rec                       0.024603    -0.043192  0.097092  -0.048105
pub_rec_bankruptcies          0.015048    -0.029963  0.082078  -0.032866
revol_bal                    -0.025706     0.315640  0.100515   0.320136
revol_util                   -0.068598     0.095136  0.465695   0.065284
total_acc                     0.113206     0.230644 -0.042612   0.255719
total_pymnt                  -0.010114     0.854238  0.313651   0.886746
total_rec_int                 0.023080     0.632747  0.531746   0.729106
total_rec_late_fee            0.029547     0.059798  0.100839   0.050447
total_rec_prncp              -0.023412     0.851132  0.193289   0.855311
days_since_first_cr_line      0.006994     0.169246 -0.093930   0.199594
days_since_last_pymnt         0.073552    -0.043235 -0.102115  -0.146459
days_since_last_cr_pull      -0.025196    -0.019885 -0.119939  -0.039591

                        open_acc   pub_rec  ...  revol_bal  revol_util  \
annual_inc              0.157171 -0.015147  ...   0.279054    0.017173
```

```
delinq_2yrs               0.011986  0.009970  ...  -0.056674   -0.044628
dti                       0.290514 -0.005554  ...   0.228631    0.276073
funded_amnt               0.172354 -0.048898  ...   0.313264    0.069696
inq_last_6mths            0.092757  0.024603  ...  -0.025706   -0.068598
installment               0.169679 -0.043192  ...   0.315640    0.095136
int_rate                  0.013577  0.097092  ...   0.100515    0.465695
loan_amnt                 0.173914 -0.048105  ...   0.320136    0.065284
open_acc                  1.000000  0.003568  ...   0.286259   -0.087536
pub_rec                   0.003568  1.000000  ...  -0.059926    0.057715
pub_rec_bankruptcies      0.009457  0.841247  ...  -0.047077    0.060246
revol_bal                 0.286259 -0.059926  ...   1.000000    0.305062
revol_util               -0.087536  0.057715  ...   0.305062    1.000000
total_acc                 0.684804 -0.020384  ...   0.312378   -0.068831
total_pymnt               0.158537 -0.050642  ...   0.295432    0.080870
total_rec_int             0.122305 -0.005121  ...   0.244697    0.195013
total_rec_late_fee       -0.016989 -0.006129  ...   0.006222    0.040979
total_rec_prncp           0.156791 -0.062609  ...   0.284513    0.026387
days_since_first_cr_line  0.208382  0.035276  ...   0.245795   -0.025639
days_since_last_pymnt    -0.027757  0.013952  ...  -0.034163   -0.090850
days_since_last_cr_pull  -0.074567 -0.052309  ...  -0.045488   -0.145986

                          total_acc  total_pymnt  total_rec_int  \
annual_inc                 0.237203     0.257571       0.185332
delinq_2yrs                0.068196    -0.023685       0.022342
dti                        0.229083     0.064530       0.104411
funded_amnt                0.249831     0.903647       0.736995
inq_last_6mths             0.113206    -0.010114       0.023080
installment                0.230644     0.854238       0.632747
int_rate                  -0.042612     0.313651       0.531746
loan_amnt                  0.255719     0.886746       0.729106
open_acc                   0.684804     0.158537       0.122305
pub_rec                   -0.020384    -0.050642      -0.005121
pub_rec_bankruptcies      -0.007656    -0.039649      -0.000577
revol_bal                  0.312378     0.295432       0.244697
revol_util                -0.068831     0.080870       0.195013
total_acc                  1.000000     0.222062       0.145692
total_pymnt                0.222062     1.000000       0.836404
total_rec_int              0.145692     0.836404       1.000000
total_rec_late_fee        -0.020286     0.021781       0.082799
total_rec_prncp            0.228903     0.971794       0.695599
days_since_first_cr_line   0.358805     0.179525       0.123714
days_since_last_pymnt     -0.003767    -0.317523      -0.474569
days_since_last_cr_pull   -0.066941    -0.023946      -0.131297

                          total_rec_late_fee  total_rec_prncp  \
annual_inc                          0.008124         0.259872
delinq_2yrs                         0.033372        -0.039953
dti                                -0.010295         0.041901
funded_amnt                         0.052480         0.874004
inq_last_6mths                      0.029547        -0.023412
installment                         0.059798         0.851132
int_rate                            0.100839         0.193289
loan_amnt                           0.050447         0.855311
open_acc                           -0.016989         0.156791
pub_rec                            -0.006129        -0.062609
pub_rec_bankruptcies               -0.005562        -0.050157
```

revol_bal	0.006222	0.284513
revol_util	0.040979	0.026387
total_acc	-0.020286	0.228903
total_pymnt	0.021781	0.971794
total_rec_int	0.082799	0.695599
total_rec_late_fee	1.000000	-0.013677
total_rec_prncp	-0.013677	1.000000
days_since_first_cr_line	-0.010749	0.183498
days_since_last_pymnt	0.008729	-0.237988
days_since_last_cr_pull	-0.026863	0.023259

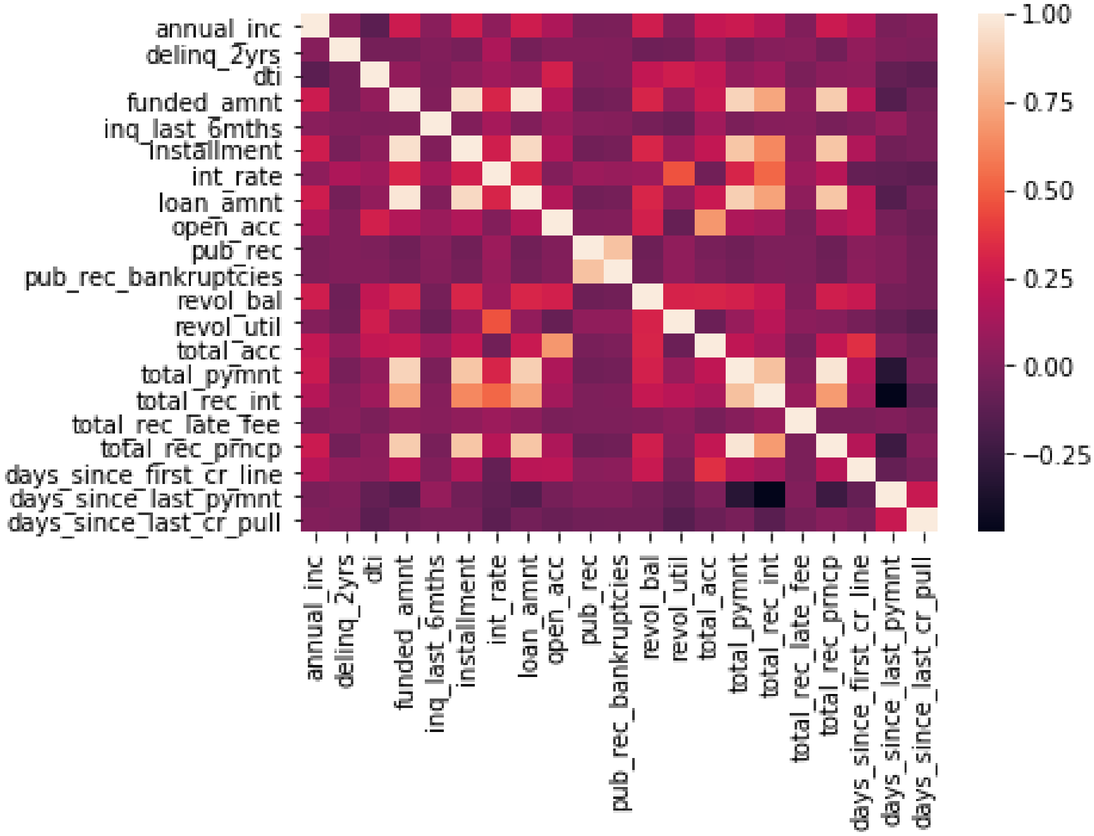
	days_since_first_cr_line	days_since_last_pymnt	\
annual_inc	0.180313	-0.015844	
delinq_2yrs	0.064830	0.005000	
dti	0.050192	-0.097698	
funded_amnt	0.193477	-0.146958	
inq_last_6mths	0.006994	0.073552	
installment	0.169246	-0.043235	
int_rate	-0.093930	-0.102115	
loan_amnt	0.199594	-0.146459	
open_acc	0.208382	-0.027757	
pub_rec	0.035276	0.013952	
pub_rec_bankruptcies	0.044421	0.012104	
revol_bal	0.245795	-0.034163	
revol_util	-0.025639	-0.090850	
total_acc	0.358805	-0.003767	
total_pymnt	0.179525	-0.317523	
total_rec_int	0.123714	-0.474569	
total_rec_late_fee	-0.010749	0.008729	
total_rec_prncp	0.183498	-0.237988	
days_since_first_cr_line	1.000000	-0.088809	
days_since_last_pymnt	-0.088809	1.000000	
days_since_last_cr_pull	-0.024030	0.246529	

	days_since_last_cr_pull
annual_inc	0.010625
delinq_2yrs	-0.007269
dti	-0.119076
funded_amnt	-0.042719
inq_last_6mths	-0.025196
installment	-0.019885
int_rate	-0.119939
loan_amnt	-0.039591
open_acc	-0.074567
pub_rec	-0.052309
pub_rec_bankruptcies	-0.046864
revol_bal	-0.045488
revol_util	-0.145986
total_acc	-0.066941
total_pymnt	-0.023946
total_rec_int	-0.131297
total_rec_late_fee	-0.026863
total_rec_prncp	0.023259
days_since_first_cr_line	-0.024030
days_since_last_pymnt	0.246529
days_since_last_cr_pull	1.000000

```
[21 rows x 21 columns]
```

In [21]:
```
sns.heatmap(X[numeric_cols].corr())
```

Out[21]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x12e128898>
```



In [22]:
```
X[['total_rec_prncp', 'total_pymnt']].corr()
```

Out[22]:

	total_rec_prncp	total_pymnt
total_rec_prncp	1.000000	0.971794
total_pymnt	0.971794	1.000000

There are some almost perfect correlation, for example total_rec_prncp, which we can take out.

In [23]:
```
X = X.drop('total_rec_prncp', axis=1)
```

d. Split the dataset into a single test and training set, a simple rule of thumb is an 40/60 split. How did you build these two sets?

In [24]:
```
from sklearn.model_selection import train_test_split

# firt convert categorical cols to dummies
cat_cols = [k for k,v in X.dtypes.to_dict().items() if v in [object]]
dummy = pd.get_dummies(X[cat_cols])
X = pd.concat([X, dummy], axis=1)
X = X.drop(cat_cols, axis=1)
```

In [25]:
```
X.shape
```

Out[25]:
```
(37901, 947)
```

In [26]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.4)
```

e. Using your training set, run a logistic regression, a random forest, and a gradient boosted random forest. To show your results, present both a measure of miscalssification error, accuracy and a confusion matrix.

In [27]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import accuracy_score, confusion_matrix

rf = RandomForestClassifier()
logit = LogisticRegression()
rfgb = GradientBoostingClassifier()
```

```
/Users/parasu/anaconda3/lib/python3.6/site-
packages/sklearn/ensemble/weight_boosting.py:29: DeprecationWarning:
numpy.core.umath_tests is an internal NumPy module and should not be imported. It will
be removed in a future NumPy release.
  from numpy.core.umath_tests import inner1d
```

In [28]:
```
logit.fit(X_train, y_train)
rf.fit(X_train, y_train)
rfgb.fit(X_train, y_train)
```

Out[28]:
```
GradientBoostingClassifier(criterion='friedman_mse', init=None,
              learning_rate=0.1, loss='deviance', max_depth=3,
              max_features=None, max_leaf_nodes=None,
              min_impurity_decrease=0.0, min_impurity_split=None,
              min_samples_leaf=1, min_samples_split=2,
              min_weight_fraction_leaf=0.0, n_estimators=100,
              presort='auto', random_state=None, subsample=1.0, verbose=0,
              warm_start=False)
```

In [29]:
```
def get_metrics(model):
    print(model)
    print("accuracy")
    print(accuracy_score(y_pred=model.predict(X_test), y_true=y_test))
    print("Confusion matrix")
    print(confusion_matrix(y_pred=model.predict(X_test), y_true=y_test))
    print('\n\n')
```

In [30]:
```
for m in (rf, logit, rfgb):
    get_metrics(m)
```

```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=10, n_jobs=1,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)
accuracy
```

```
0.9389881933909373
Confusion matrix
[[ 1251   840]
 [   85 12985]]



LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
accuracy
0.9827847767297672
Confusion matrix
[[ 1832   259]
 [    2 13068]]



GradientBoostingClassifier(criterion='friedman_mse', init=None,
              learning_rate=0.1, loss='deviance', max_depth=3,
              max_features=None, max_leaf_nodes=None,
              min_impurity_decrease=0.0, min_impurity_split=None,
              min_samples_leaf=1, min_samples_split=2,
              min_weight_fraction_leaf=0.0, n_estimators=100,
              presort='auto', random_state=None, subsample=1.0, verbose=0,
              warm_start=False)
accuracy
0.9779038322010422
Confusion matrix
[[ 1779   312]
 [   23 13047]]
```

The accuracy seems suspiciously high (the baserate for paid off loan is 86%). Maybe there's leakage from one of the included variables.

f. One easy way to improve model performance is cross-validation. Do a k-fold cross validation, where k=5, using the best performing model from part (e.). Re-report the misclassification error, accuracy and a confusion matrix.

```
In [31]: from sklearn.model_selection import cross_validate, cross_val_score, cross_val_predict
```

```
In [32]: # accuracies
         cross_val_score(logit, X, y, cv=5)
```

```
Out[32]: array([0.98720485, 0.98680913, 0.98562005, 0.98139842, 0.98113208])
```

```
In [33]: confusion_matrix(y_pred=cross_val_predict(logit, X, y, cv=5), y_true=y)
```

```
Out[33]: array([[ 4663,   581],
                [    9, 32648]])
```