Problem 6

In [626]:

```
hw3 = pd.read_csv("hw3_dataset.txt", delim_whitespace=True, names = ['id', 'fund
ing', 'fv', 'shares', 'l_buyout'])
```

6 A

Trying out EDA

In [630]:

```
hw3.describe()
```

Out[630]:

	funding	fv	shares	l_buyout
count	482.000000	4.820000e+02	4.820000e+02	482.000000
mean	0.439834	2.651672e+07	2.227942e+06	0.093361
std	0.496883	2.632174e+07	1.413872e+06	0.291240
min	0.000000	1.200000e+06	3.000000e+05	0.000000
25%	0.000000	1.025000e+07	1.300000e+06	0.000000
50%	0.000000	1.950000e+07	2.000000e+06	0.000000
75%	1.000000	3.250000e+07	2.700000e+06	0.000000
max	1.000000	2.346000e+08	1.101862e+07	1.000000

The fv and shares features have really large values compared to l_buyout and funding columns.

In [627]:

```
hw3.head()
```

Out[627]:

	id	funding	fv	shares	l_buyout
0	1	0	1200000	3000000	0
1	2	0	1454000	1454000	1
2	3	0	1500000	300000	0
3	4	0	1530000	510000	0
4	5	0	2000000	800000	0

In [628]:

```
"""
we know that id is not giving any useful information
also, we'll check for missing values here
"""

hw3 = hw3.drop('id', axis=1)
nas = hw3.isnull().sum()
print(nas)
```

```
funding     0
fv          0
shares      0
l_buyout    0
dtype: int64
```

There are no missing values in this dataset

In [632]:

```
features = hw3.drop('funding', axis=1)
target = hw3['funding']
```

In [633]:

```
X_train, X_test, y_train, y_test = train_test_split(features, target, test_size=
0.33, random_state=42)
```

In [634]:

```
X_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 322 entries, 157 to 102
Data columns (total 3 columns):
fv           322 non-null int64
shares       322 non-null int64
l_buyout     322 non-null int64
dtypes: int64(3)
memory usage: 10.1 KB
```

In [635]:

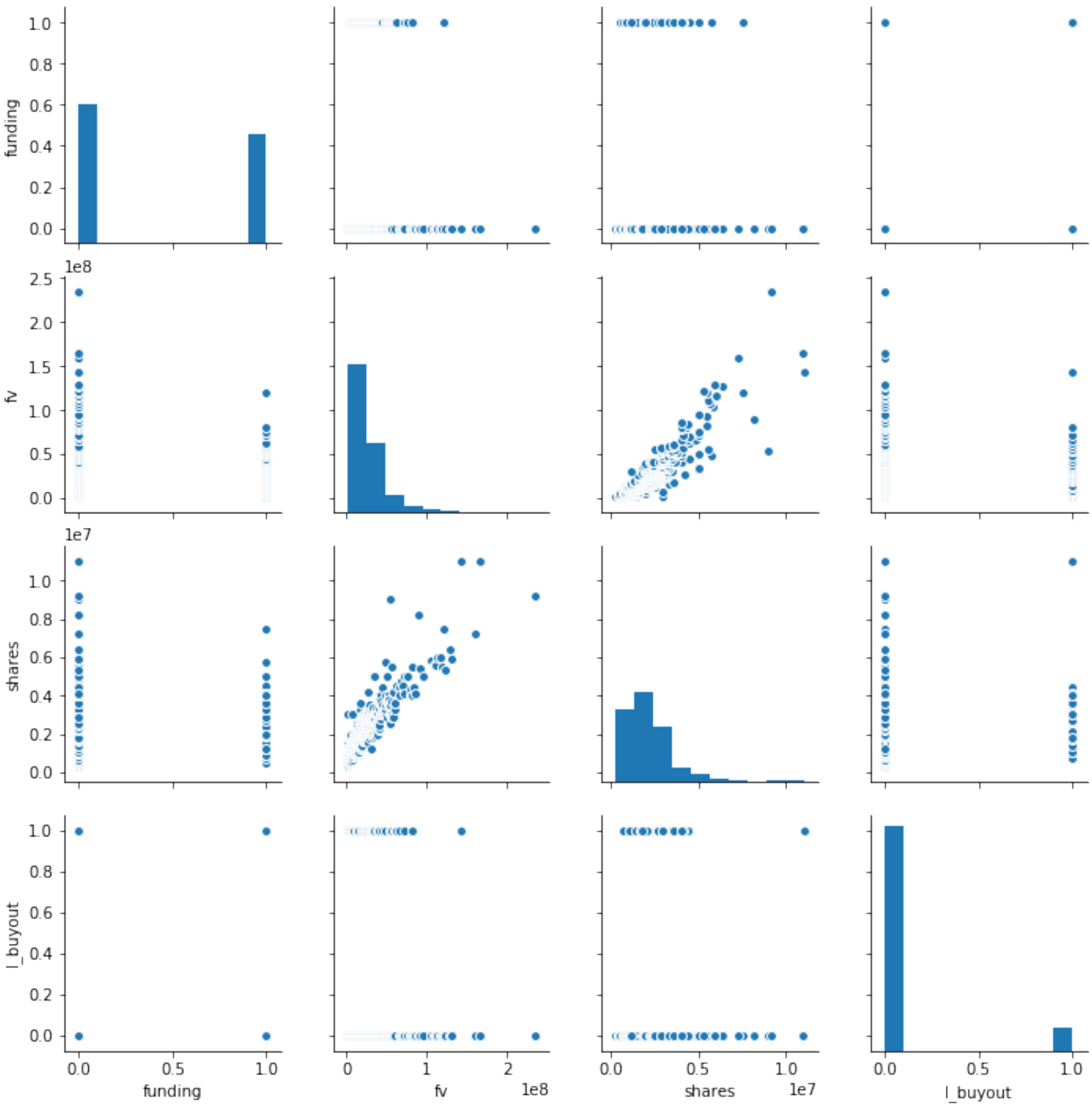
```
X_train.head()
```

Out[635]:

	fv	shares	l_buyout
157	13000000	1300000	0
449	63000000	4500000	1
118	10103125	1325000	0
114	9625000	1375000	0
439	55000000	2500000	0

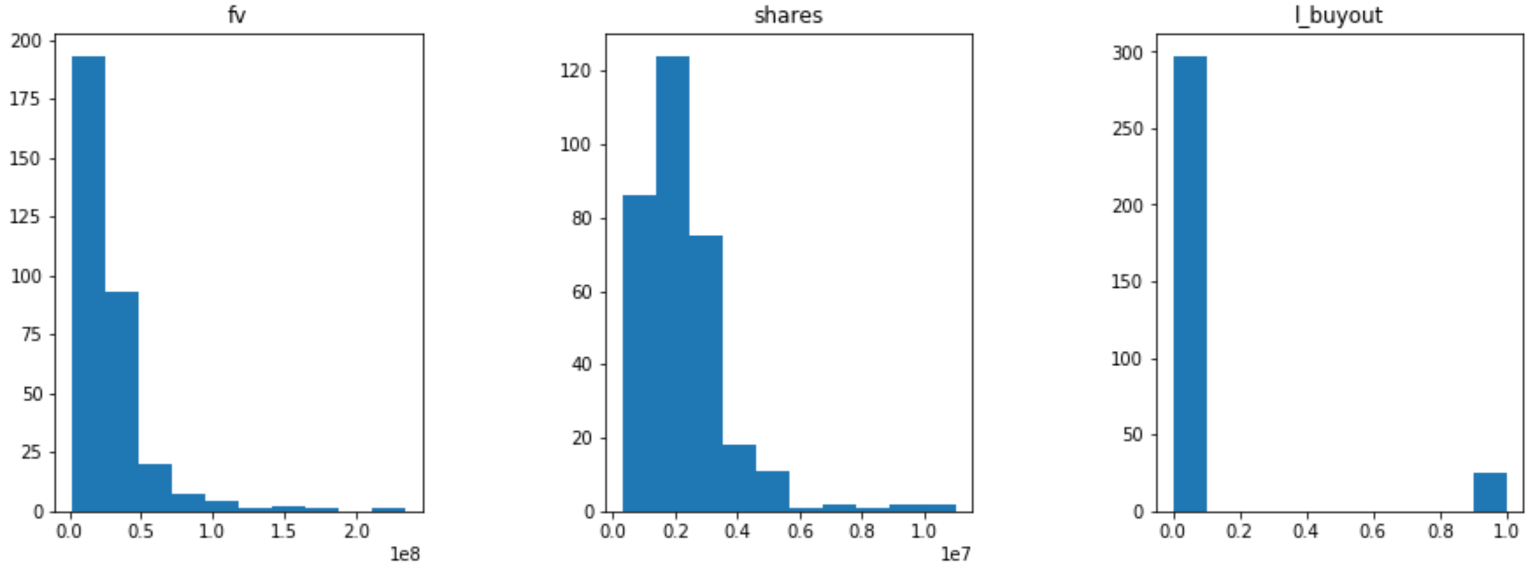
In [653]:

```
sns.pairplot(hw3, vars=hw3.columns)
plt.show()
```


funding
fv
shares
l_buyout
1e8
1e7
1e8
1e7
0.0
0.2
0.4
0.6
0.8
1.0
0.5
1.5
2.0
2.5
0
1
2

In [644]:

```
fig, axs = plt.subplots(1,3, figsize=(15, 5), facecolor='w', edgecolor='k')
fig.subplots_adjust(hspace = .5, wspace=.5)

for i,j in enumerate(X_train.columns):
    axs[i].hist(X_train[j])
    axs[i].set_title(j)
```

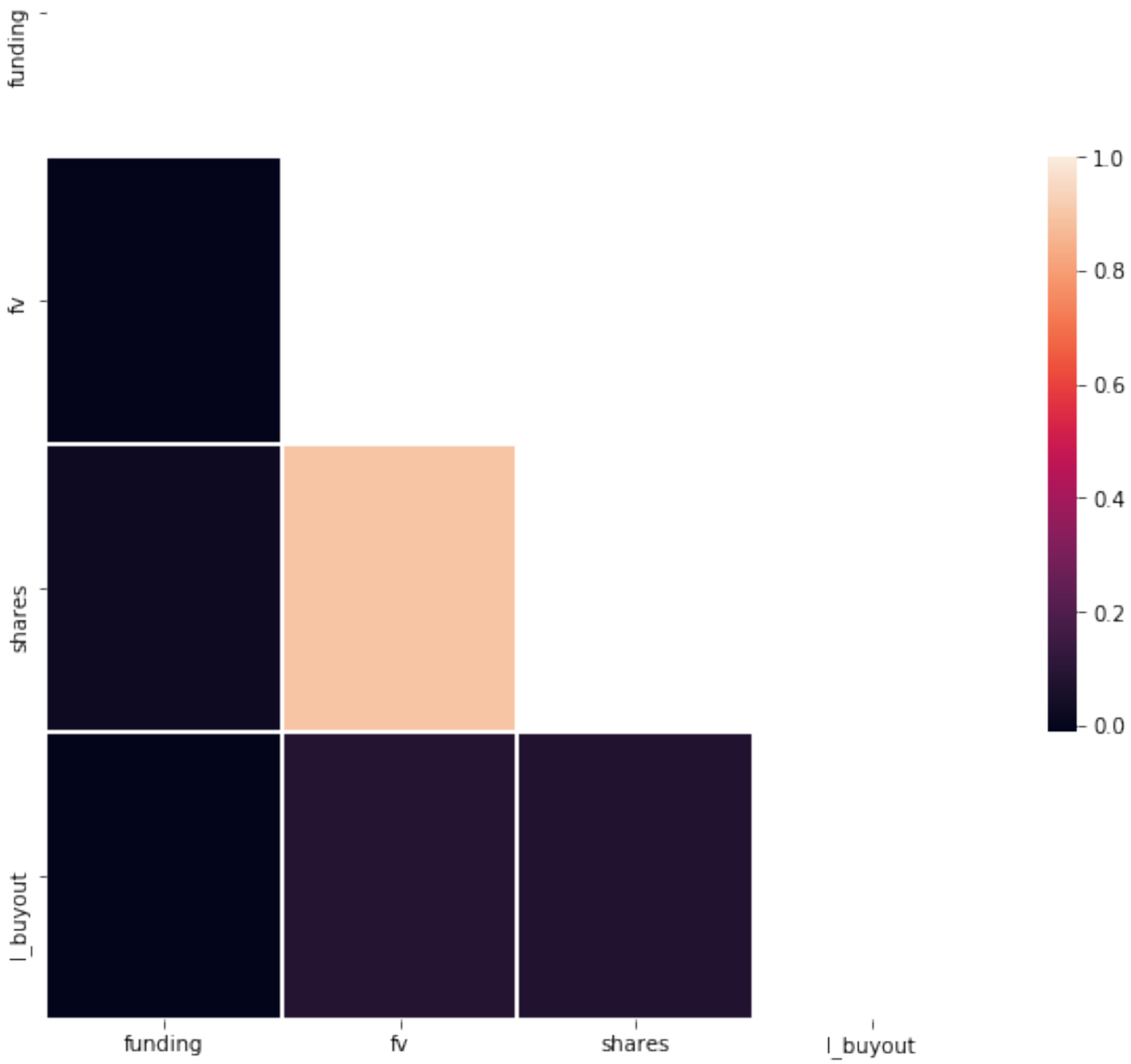


In [649]:

```
corr = hw3.corr()
mask = np.zeros_like(corr, dtype = np.bool)
mask[np.triu_indices_from(mask)] = True
plt.subplots(figsize = (10, 10))
sns.heatmap(corr, mask = mask, xticklabels = 1,
            yticklabels = 1, linewidths = 1, cbar_kws = {"shrink": .5})
```

Out[649]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f01443329b0>
```


funding
fv
shares
l_buyout
funding
fv
shares
l_buyout
1.0
0.8
0.6
0.4
0.2
0.0

Inference

In [654]:

```
X_train.head()
```

Out[654]:

	fv	shares	l_buyout
157	13000000	1300000	0
449	63000000	4500000	1
118	10103125	1325000	0
114	9625000	1375000	0
439	55000000	2500000	0

6 B

In [ ]:

```
X_train['capital'] = np.log(X_train['face_value'] * X_train['n_shares'])
X_validate['capital'] = np.log(X_validate['face_value'] * X_validate['n_shares']
)
X_test['capital'] = np.log(X_test['face_value'] * X_test['n_shares'])

X_train['fvl'] = np.log(X_train.face_value)
X_train['nsl'] = np.log(X_train.n_shares)

X_validate['fvl'] = np.log(X_validate.face_value)
X_validate['nsl'] = np.log(X_validate.n_shares)

X_test['fvl'] = np.log(X_test.face_value)
X_test['nsl'] = np.log(X_test.n_shares)
```

The first thing to try is the log value of the two features which have a positively skewed distr.

In [660]:

```
X_train['fv_log'] = np.log(X_train['fv'])
X_test['fv_log'] = np.log(X_test['fv'])
X_train['shares_log'] = np.log(X_train['shares'])
X_test['shares_log'] = np.log(X_test['shares'])
```

```
/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:4: Sett
ingWithCopyWarning:
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/panda
s-docs/stable/indexing.html#indexing-view-versus-copy
  after removing the cwd from sys.path.
/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:5: Sett
ingWithCopyWarning:
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/panda
s-docs/stable/indexing.html#indexing-view-versus-copy
  """
```

In [710]:

```
# method to print basic metrics of a classifier
def print_metrics(y_test, y_hat):
    print("Accuracy of model is ", metrics.accuracy_score(y_test, y_hat))
    print("Precision of model is ", metrics.precision_score(y_test, y_hat))
    print("Recall of model is ", metrics.recall_score(y_test, y_hat))
    print("Confusion matrix\n", metrics.confusion_matrix(y_test, y_hat))

# method to plot AUC
def plot_roc_auc(model, X_test):
    y_hat_probabilities = model.predict_proba(X_test)[::,1]
    fpr, tpr, _ = metrics.roc_curve(y_test,  y_hat_probabilities)
    auc = metrics.roc_auc_score(y_test, y_hat_probabilities)
    plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
    plt.legend(loc=4)
    plt.show()
```

In [711]:

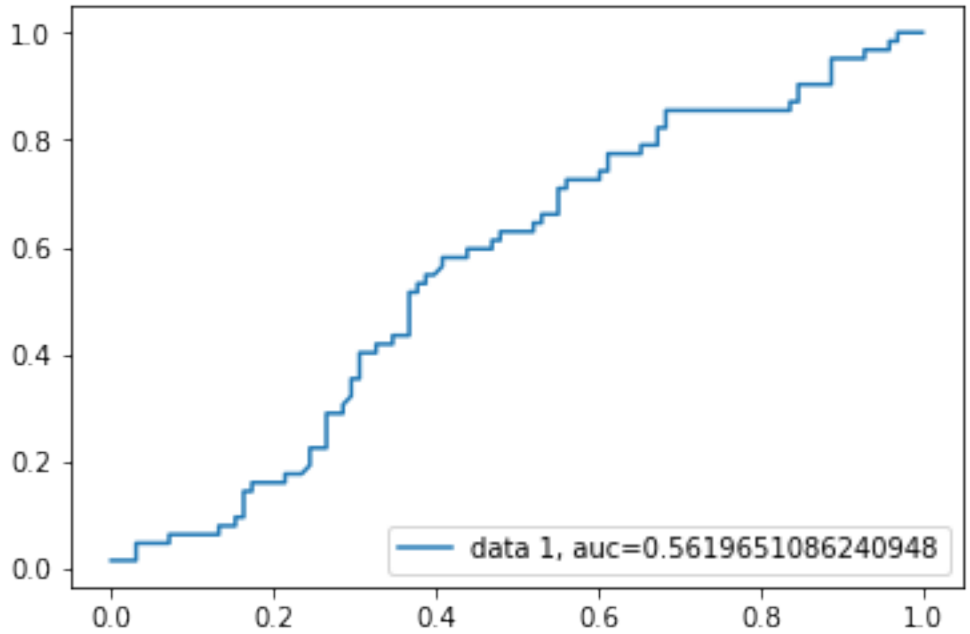
```
lr = LogisticRegression()
lr.fit(X_train[['fv_log', 'shares_log', 'l_buyout']], y_train)

y_hat = lr.predict(X_test[['fv_log', 'shares_log', 'l_buyout']])
print_metrics(y_test, y_hat)
```

```
Accuracy of model is  0.5625
Precision of model is  0.43333333333333335
Recall of model is  0.41935483870967744
Confusion matrix
 [[64 34]
 [36 26]]
```

So, that's an okayish accuracy. We just tried all variables we thought would work. Let's try plotting the Area under curve.

In [712]:

```
plot_roc_auc(lr, X_test[['fv_log', 'shares_log', 'l_buyout']])
```



Let's try more feature transformation. Since face_value and number of shares are highly correlated in stock market, it's worth trying. Moreover, there's no point in using two highly correlated features in building a model. the correlation between them is greater than 0.8. I will multiply them and then take a log over the multiplied quantity.

In [713]:

```
# All the values are greater than 0 so no need to do log(p+1) as shown in class.

X_train['stock_value'] = np.log((X_train['fv'] * X_train['shares']))
X_test['stock_value'] = np.log((X_test['fv'] * X_test['shares']))
```

```
/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:4: Sett
ingWithCopyWarning:
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/panda
s-docs/stable/indexing.html#indexing-view-versus-copy
  after removing the cwd from sys.path.
```

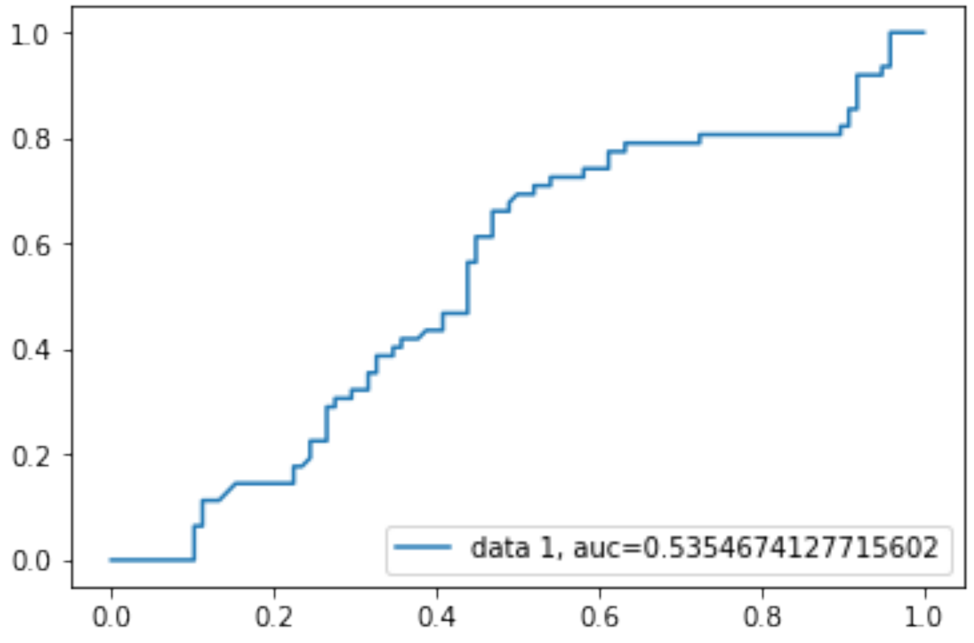
In [714]:

```
lr = LogisticRegression()
lr.fit(X_train[['stock_value', 'l_buyout']], y_train)

y_hat = lr.predict(X_test[['stock_value', 'l_buyout']])
print_metrics(y_test, y_hat)
```

```
Accuracy of model is  0.55625
Precision of model is  0.0
Recall of model is  0.0
Confusion matrix
 [[89  9]
 [62  0]]
```

In [715]:

```
plot_roc_auc(lr, X_test[['stock_value', 'l_buyout']])
```



Didn't give a significant improvement. Logistic regression has different solver so will try a different solver.

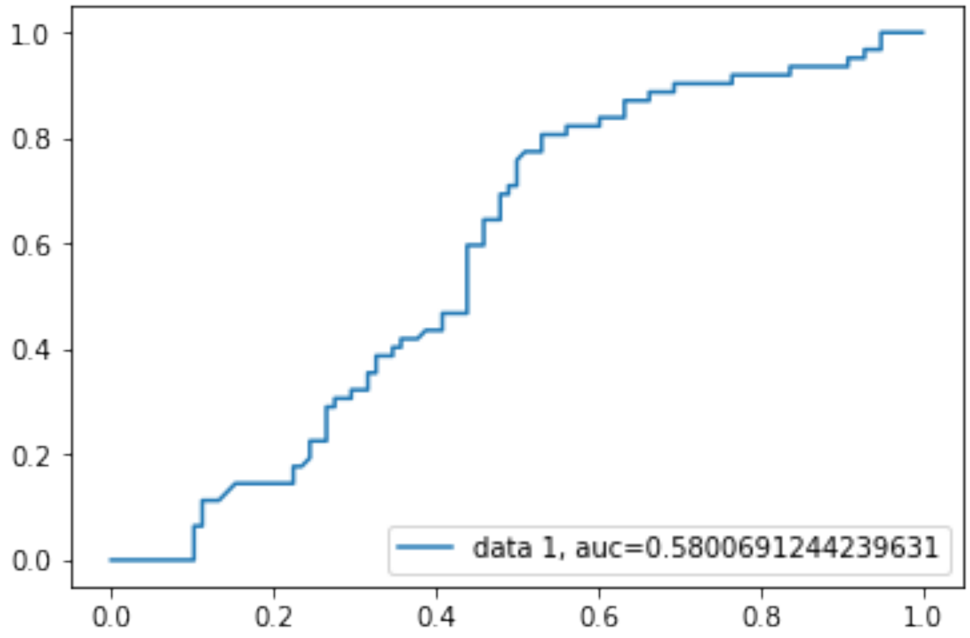
In [736]:

```
lr = LogisticRegression(solver='lbfgs')
lr.fit(X_train[['stock_value', 'l_buyout']], y_train)

y_hat = lr.predict(X_test[['stock_value', 'l_buyout']])
print_metrics(y_test, y_hat)
```

```
Accuracy of model is  0.55
Precision of model is  0.4074074074074074
Recall of model is  0.3548387096774194
Confusion matrix
 [[66 32]
 [40 22]]
```

In [717]:

```
plot_roc_auc(lr, X_test[['stock_value', 'l_buyout']])
```



Though it didn't improve significantly, it is definitely better than the previous model.

6 C

Now, we try another kind of classifier- LDA. Again following a similar approach, let's start with all features and slowly narrow down to the ones which we found useful from our logistic regression model.

In [718]:

```
lda = sklearn_lda()
lda.fit(X_train[['fv_log', 'shares_log', 'l_buyout']], y_train)

y_hat = lda.predict(X_test[['fv_log', 'shares_log', 'l_buyout']])
print_metrics(y_test, y_hat)
```

```
Accuracy of model is  0.575
Precision of model is  0.45
Recall of model is  0.43548387096774194
Confusion matrix
 [[65 33]
 [35 27]]
```

Now, trying the enhanced version:

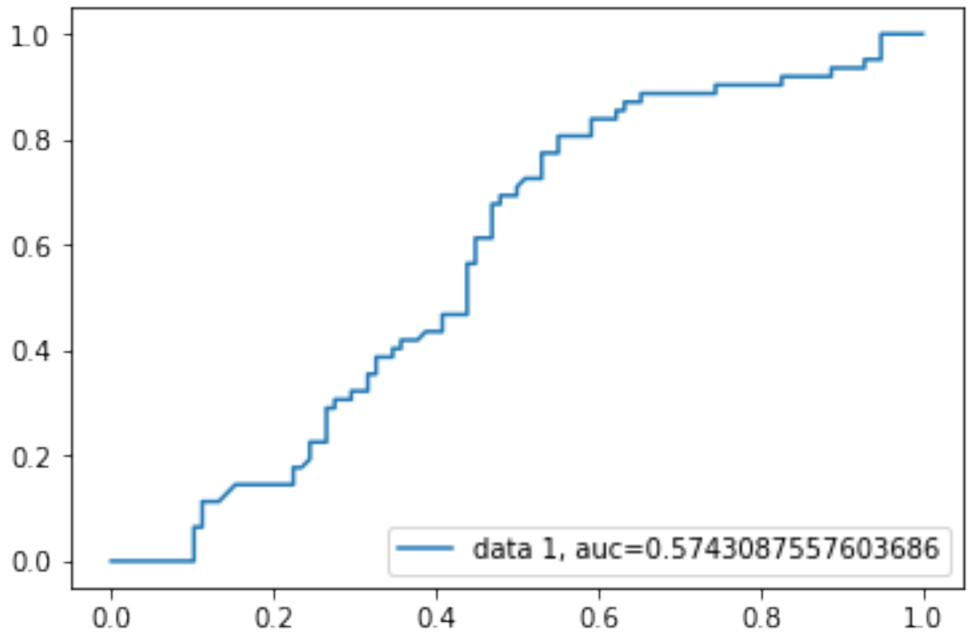
In [719]:

```
lda = sklearn_lda()
lda.fit(X_train[['stock_value', 'l_buyout']], y_train)

y_hat = lda.predict(X_test[['stock_value', 'l_buyout']])
print_metrics(y_test, y_hat)
```

```
Accuracy of model is  0.55
Precision of model is  0.4074074074074074
Recall of model is  0.3548387096774194
Confusion matrix
 [[66 32]
 [40 22]]
```

In [720]:

```
plot_roc_auc(lda, X_test[['stock_value', 'l_buyout']])
```



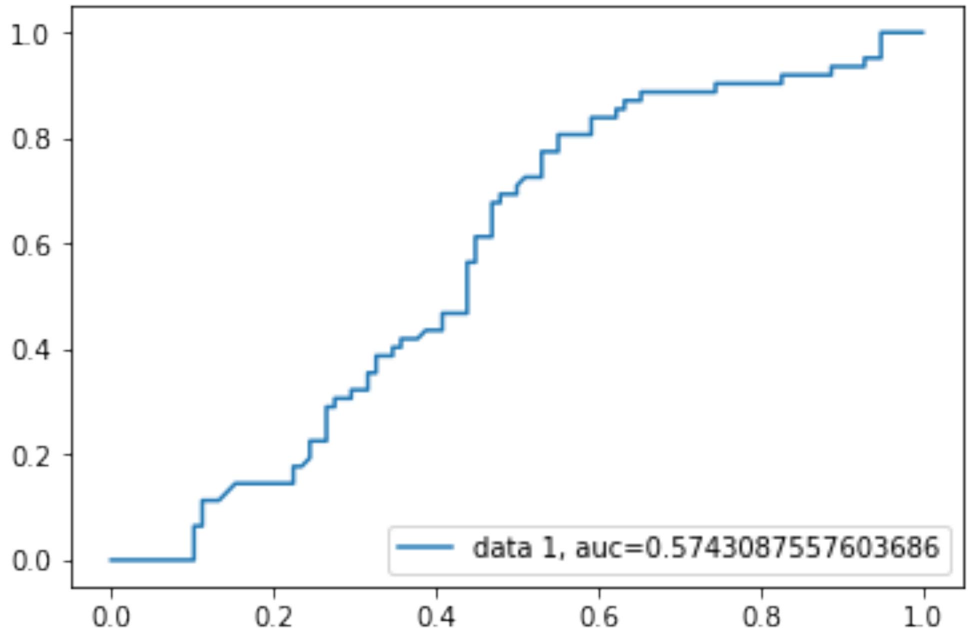
In [731]:

```
lda = sklearn_lda(solver='svd')
lda.fit(X_train[['stock_value', 'l_buyout']], y_train)

y_hat = lda.predict(X_test[['stock_value', 'l_buyout']])
print_metrics(y_test, y_hat)
```

```
Accuracy of model is  0.55
Precision of model is  0.4074074074074074
Recall of model is  0.3548387096774194
Confusion matrix
 [[66 32]
 [40 22]]
```

In [732]:

```
plot_roc_auc(lda, X_test[['stock_value', 'l_buyout']])
```



Let's even test the training accuracy of our model

In [723]:

```
y_hat_train = lda.predict(X_train[['stock_value', 'l_buyout']])
print_metrics(y_train, y_hat_train)
```

```
Accuracy of model is  0.5807453416149069
Precision of model is  0.5619834710743802
Recall of model is  0.4533333333333333
Confusion matrix
 [[119  53]
 [ 82  68]]
```

Here, we observe again that feature transformation provides better AUC compared to fitting the model on the original features. However, changing solver here didn't make any difference.

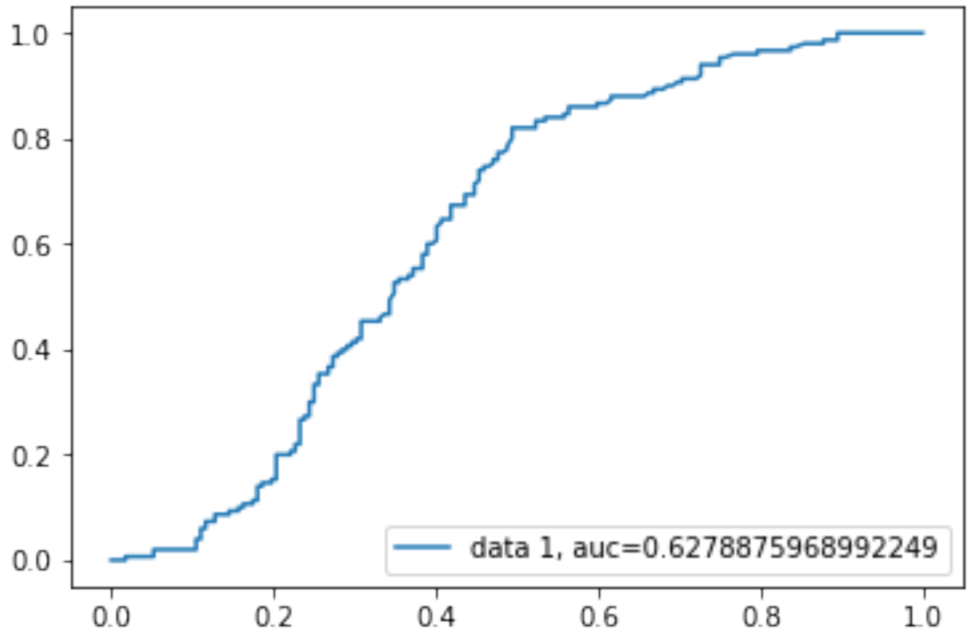
6 D

Let's try finding training accuracies:
a) Logistic regression

In [725]:

```
lr = LogisticRegression(solver='lbfgs')
lr.fit(X_train[['stock_value', 'l_buyout']], y_train)

y_hat_train = lr.predict(X_train[['stock_value', 'l_buyout']])
print_metrics(y_train, y_hat_train)

y_hat_probabilities = lr.predict_proba(X_train[['stock_value', 'l_buyout']])[::,
1]
fpr, tpr, _ = metrics.roc_curve(y_train,  y_hat_probabilities)
auc = metrics.roc_auc_score(y_train, y_hat_probabilities)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```

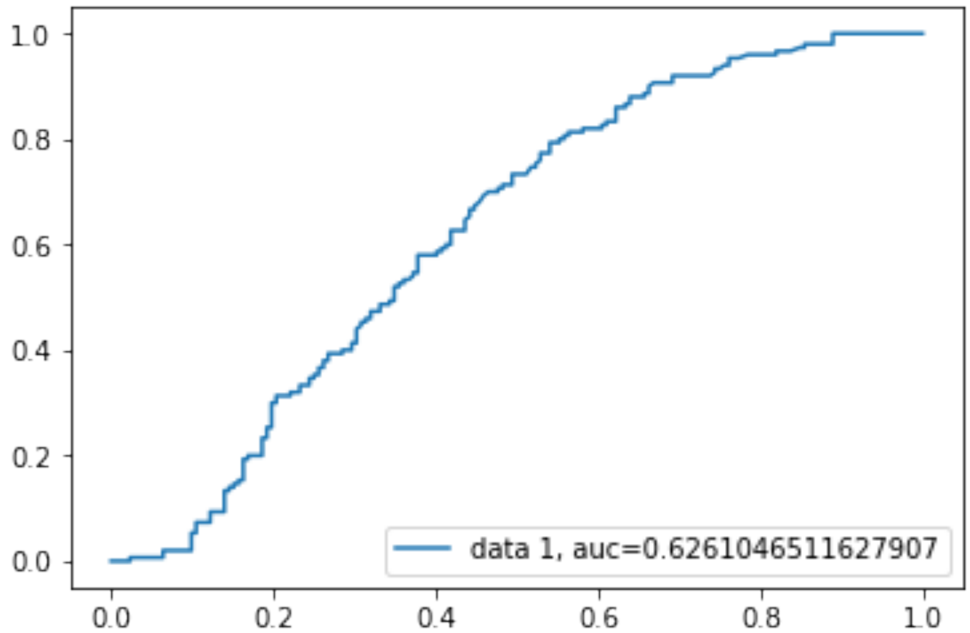
```
Accuracy of model is  0.5745341614906833
Precision of model is  0.5546218487394958
Recall of model is  0.44
Confusion matrix
 [[119  53]
 [ 84  66]]
```



In [727]:

```
lr = LogisticRegression(solver='lbfgs')
lr.fit(X_train[['fv_log', 'l_buyout', 'shares_log']], y_train)

y_hat_train = lr.predict(X_train[['fv_log', 'l_buyout', 'shares_log']])
print_metrics(y_train, y_hat_train)

y_hat_probabilities = lr.predict_proba(X_train[['fv_log', 'l_buyout', 'shares_lo
g']])[::,1]
fpr, tpr, _ = metrics.roc_curve(y_train,  y_hat_probabilities)
auc = metrics.roc_auc_score(y_train, y_hat_probabilities)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```

```
Accuracy of model is  0.5838509316770186
Precision of model is  0.5634920634920635
Recall of model is  0.47333333333333333
Confusion matrix
 [[117  55]
 [ 79  71]]
```

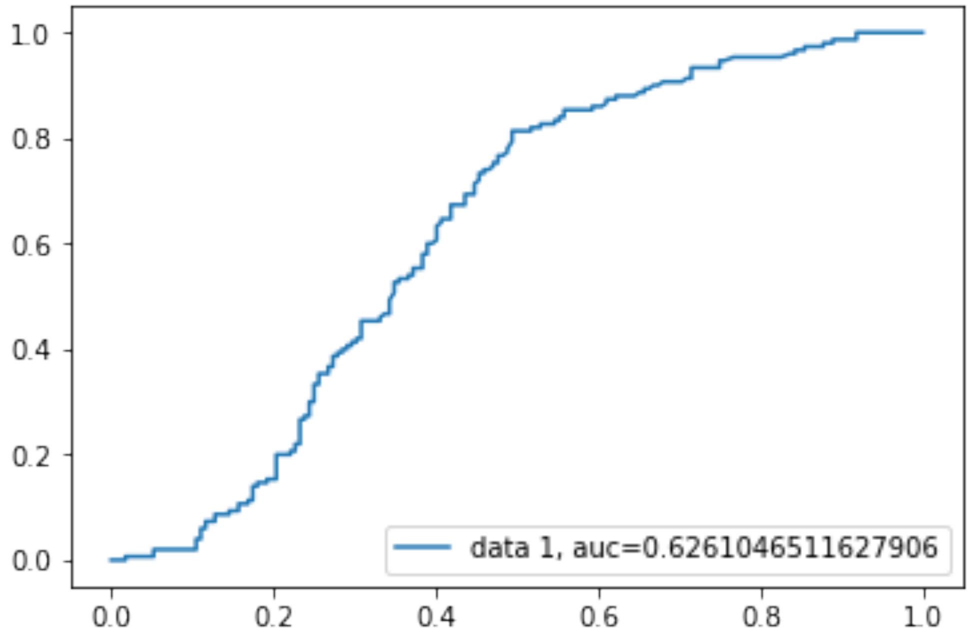


b) Linear Discriminant Analysis

In [737]:

```
lda = sklearn_lda(solver='svd')
lda.fit(X_train[['stock_value', 'l_buyout']], y_train)

y_hat_train = lda.predict(X_train[['stock_value', 'l_buyout']])
print_metrics(y_train, y_hat_train)

y_hat_probabilities = lda.predict_proba(X_train[['stock_value', 'l_buyout']])[::
,1]
fpr, tpr, _ = metrics.roc_curve(y_train,  y_hat_probabilities)
auc = metrics.roc_auc_score(y_train, y_hat_probabilities)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```

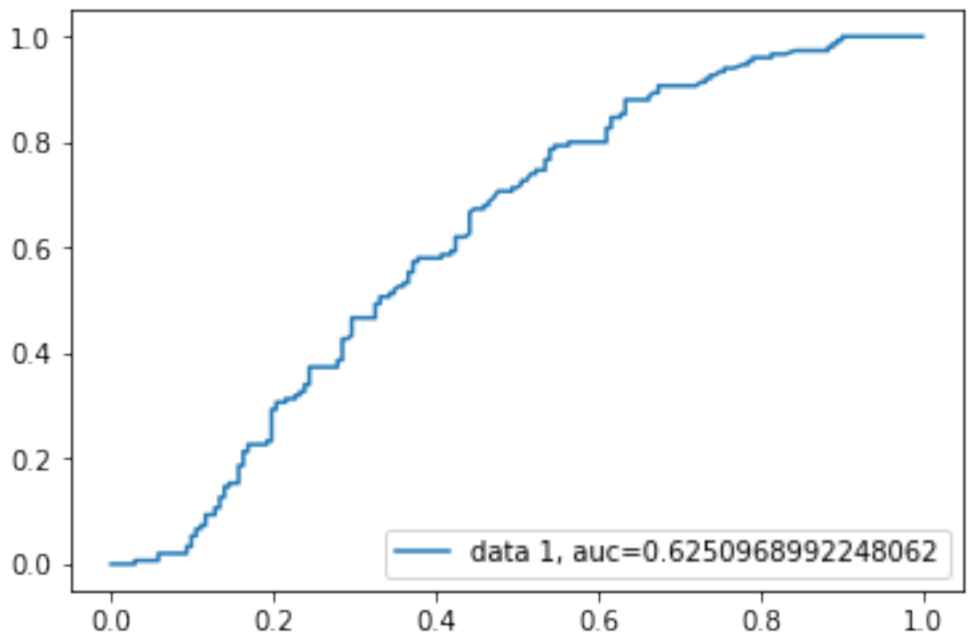
```
Accuracy of model is  0.5807453416149069
Precision of model is  0.5619834710743802
Recall of model is  0.4533333333333333
Confusion matrix
 [[119  53]
 [ 82  68]]
```



In [738]:

```
lda = sklearn_lda(solver='svd')
lda.fit(X_train[['fv_log', 'l_buyout', 'shares_log']], y_train)

y_hat_train = lda.predict(X_train[['fv_log', 'l_buyout', 'shares_log']])
print_metrics(y_train, y_hat_train)

y_hat_probabilities = lda.predict_proba(X_train[['fv_log', 'l_buyout', 'shares_l
og']])[::,1]
fpr, tpr, _ = metrics.roc_curve(y_train,  y_hat_probabilities)
auc = metrics.roc_auc_score(y_train, y_hat_probabilities)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```

```
Accuracy of model is  0.5900621118012422
Precision of model is  0.5671641791044776
Recall of model is  0.5066666666666667
Confusion matrix
 [[114  58]
 [ 74  76]]
```



Here I tested out traning accuracies in my model.