AngelList_ML_Python

June 23, 2016

```
In [1]: from urllib import urlencode
        import urllib2
        import json
        import requests
        import pandas as pd
        import matplotlib.pyplot as plt
        import numpy as np
```

1 #The individual frame; first page of startups on angellist site

```
In [2]: #loop through pages(here two) and extract the startups/individ fields info and add to DF;
        #does not matter what page it comes from
        urls = 'https://api.angel.co/1/startups?filter=raising&page='
        fields = ['id','name','created_at','high_concept','quality','updated_at','company_url',
                  'video_url','twitter_url','linkedin_url','facebook_url','thumb_url','blog_url',
                  'community_profile','product_desc','launch_date','hidden','follower_count',
                  'angellist_url',
                  'logo_url','company_size']
        l=list()
        for i in range(1,2):
            r = requests.get(urls+str(i))
            t = r.json()
            startups = t['startups']
            for j in range(0,len(startups)):
                comp = startups[j]
                l.append(comp)
        indiv = pd.DataFrame(l,columns = fields)

        #this works perfectly
        #same thing for the composed fields dataframes,
        #uniquely identified by company field and name
```

```
In [6]: #Now get the fundraising data frame
```

```
In [ ]: urls = 'https://api.angel.co/1/startups?filter=raising&page='
        l=list()
        for i in range(1,9):
            r = requests.get(urls+str(i))
            t = r.json()
            startups = t['startups']
            for j in range(0,len(startups)):
                comp = startups[j]
                d = comp['fundraising']
```

```
            d['name']=comp['name']
            d['id']=comp['id']
            l.append(d)
    fund = pd.DataFrame(l)
    #this works very well in a minute or so to extract the fundraising dataframe
```

In [289]: fund.shape

Out[289]: (400, 10)

In [189]: indiv.columns

Out[189]: Index([u'id', u'name', u'created_at', u'high_concept', u'quality', u'updated_at', u'company_url

In [288]: indiv.shape

Out[288]: (400, 21)

In [191]: indiv.head()

```
Out[191]:        id               name            created_at  \
          0  389582      CoffeetheApp  2014-04-29T20:07:33Z
          1  293071      Wear My Tags  2013-11-11T23:09:59Z
          2  235684  The Cherry Share  2013-07-17T11:31:00Z
          3  144128       Vidinterest  2012-12-05T11:47:08Z
          4  355204    UberOnTime.com  2014-03-05T18:58:10Z

                                           high_concept  quality  \
          0                  Professional Networking for Jobs        4
          1                       Fashion Sourcing Made Easy!        6
          2  your way to find the healthiest and best price...        5
          3       Online Video Discovery & Promotion Platform        4
          4                                 On Demand Postman        4

                      updated_at                       company_url  \
          0  2014-12-16T17:08:52Z            http://coffeetheapp.com
          1  2014-12-17T05:38:42Z  http://wearmytags.com/development/
          2  2014-12-17T01:51:15Z      http://www.thecherryshare.com/
          3  2014-12-12T19:54:29Z              http://vidinterest.tv
          4  2014-12-11T16:16:46Z              http://uberontime.com

                                                   video_url  \
          0        https://www.youtube.com/watch?v=4ShUlSzxwWg
          1  https://www.youtube.com/watch?v=44Xj8bRnoWA&fe...
          2  http://www.youtube.com/watch?v=8QJQ9F8atOQ&fea...
          3
          4

                               twitter_url  \
          0  https://twitter.com/coffeetheapp
          1    https://twitter.com/WearMyTags
          2        http://twitter.com/foodlve
          3    http://twitter.com/vidinterest
          4     http://twitter.com/uberontime

                                           linkedin_url  \
```

```
0  https://www.linkedin.com/company/5078073?trk=p...
1
2
3
4

                        ...                            \
0                       ...
1                       ...
2                       ...
3                       ...
4                       ...

                                          thumb_url  \
0  https://d1qb2nb5cznatu.cloudfront.net/startups...
1  https://d1qb2nb5cznatu.cloudfront.net/startups...
2  https://d1qb2nb5cznatu.cloudfront.net/startups...
3  https://d1qb2nb5cznatu.cloudfront.net/startups...
4  https://d1qb2nb5cznatu.cloudfront.net/startups...

                        blog_url community_profile  \
0                                             False
1                                             False
2  http://www.thecherryshare.com/             False
3     http://blog.vidinterest.com             False
4      http://uberontime.com/blog             False

                                       product_desc launch_date hidden  \
0  Coffeetheapp is a mobile community of hiring m...  2014-07-01  False
1  WearMyTags.com solves the fashion/apparel indu...  2014-07-01  False
2  The Cherry Share is a mobile and web applicati...  2012-06-01  False
3  Vidinterest lets you discover and create priva...  2012-06-01  False
4  On-demand postman delivers packages locally.  ...  2014-06-01  False

  follower_count                     angellist_url  \
0             48      https://angel.co/coffeetheapp
1             97      https://angel.co/wear-my-tags
2             36  https://angel.co/the-cherry-share
3             19       https://angel.co/vidinterest
4              5    https://angel.co/uberontime-com

                                           logo_url company_size
0  https://d1qb2nb5cznatu.cloudfront.net/startups...         1-10
1  https://d1qb2nb5cznatu.cloudfront.net/startups...         1-10
2  https://d1qb2nb5cznatu.cloudfront.net/startups...         1-10
3  https://d1qb2nb5cznatu.cloudfront.net/startups...         1-10
4  https://d1qb2nb5cznatu.cloudfront.net/startups...         1-10

[5 rows x 21 columns]
```

In [28]:
```
#create new variables in indiv df based on presence or absence of links
```

In [290]:
```
indiv['website'] = (indiv['company_url'].fillna('')) != ''
#this checks for Nan and none and blanks but not for incomplete or incorrect
```

In [117]:
```
#same check for facebook_url
```

In [291]: indiv['facebook']= (indiv['facebook_url'].fillna('')) != ''

In [119]: #check for linkedin link

In [292]: indiv['linkedin'] = (indiv['linkedin_url'].fillna('')) != ''

In [124]: #check for twitter link

In [293]: indiv['twitter'] = (indiv['twitter_url'].fillna('')) != ''

In [294]: indiv['blog'] = (indiv['blog_url'].fillna('')) != ''

In [140]: #create new data frame with a combination of columns from indiv and fund;
#first merge the two by company id;

In [295]: df_merged = pd.merge(indiv,fund, on = 'id', how = 'outer')

In [296]: df_merged.shape

Out[296]: (400, 35)

In [297]: df_merged.head()

Out[297]:

```
       id           name_x            created_at  \
0  389582      CoffeetheApp  2014-04-29T20:07:33Z
1  293071       Wear My Tags  2013-11-11T23:09:59Z
2  235684  The Cherry Share  2013-07-17T11:31:00Z
3  144128       Vidinterest  2012-12-05T11:47:08Z
4  355204    UberOnTime.com  2014-03-05T18:58:10Z

                                        high_concept  quality  \
0                    Professional Networking for Jobs        4
1                         Fashion Sourcing Made Easy!        6
2  your way to find the healthiest and best price...        5
3       Online Video Discovery & Promotion Platform         4
4                                   On Demand Postman        4

           updated_at_x                     company_url  \
0  2014-12-16T17:08:52Z           http://coffeetheapp.com
1  2014-12-17T05:38:42Z  http://wearmytags.com/development/
2  2014-12-17T01:51:15Z      http://www.thecherryshare.com/
3  2014-12-12T19:54:29Z             http://vidinterest.tv
4  2014-12-11T16:16:46Z            http://uberontime.com

                                          video_url  \
0        https://www.youtube.com/watch?v=4ShUlSzxwWg
1  https://www.youtube.com/watch?v=44Xj8bRnoWA&fe...
2  http://www.youtube.com/watch?v=8QJQ9F8at0Q&fea...
3
4

                      twitter_url  \
0  https://twitter.com/coffeetheapp
1    https://twitter.com/WearMyTags
2        http://twitter.com/foodlve
3    http://twitter.com/vidinterest
```

```
4     http://twitter.com/uberontime

                                      linkedin_url  \
0  https://www.linkedin.com/company/5078073?trk=p...
1
2
3
4

                        ...                              blog discount  \
0                       ...                             False      NaN
1                       ...                             False      NaN
2                       ...                              True      NaN
3                       ...                              True      NaN
4                       ...                              True      NaN

  equity_basis            name_y pre_money_valuation public raised_amount  \
0       equity      CoffeetheApp             3000000   True             0
1       equity      Wear My Tags                 NaN   True             0
2       equity  The Cherry Share             3000000   True         91000
3       equity       Vidinterest             1000000   True             0
4       equity     UberOnTime.com            1000000   True             0

   raising_amount round_opened_at          updated_at_y
0          250000      2014-12-15  2014-12-15T19:55:19Z
1          750000      2014-12-14  2014-12-17T01:58:36Z
2          400000      2014-12-14  2014-12-14T06:20:03Z
3          100000      2014-12-12  2014-12-12T19:58:06Z
4          100000      2014-12-11  2014-12-11T16:12:13Z

[5 rows x 35 columns]
```

In [201]:
```
df_merged.columns
```

Out[201]:
```
Index([u'id', u'name_x', u'created_at', u'high_concept', u'quality', u'updated_at_x', u'company
```

In [145]:
```
#get the dataframe to be used for meetup analytics, visualiz and scikit learn
```

In [298]:
```
ana = df_merged[['id','name_x','high_concept','product_desc','launch_date','created_at',
                 'follower_count','quality','company_size','twitter','linkedin','facebook',
                 'website','blog','discount','equity_basis','pre_money_valuation',
                 'raised_amount',
                 'round_opened_at','raising_amount']]
```

In [299]:
```
del indiv
```

In [300]:
```
del fund
```

In [301]:
```
del df_merged
```

In [302]:
```
ana.head()
```

Out[302]:
```
       id            name_x  \
0  389582      CoffeetheApp
1  293071      Wear My Tags
2  235684  The Cherry Share
```

```
3  144128       Vidinterest
4  355204    UberOnTime.com

                                        high_concept  \
0                    Professional Networking for Jobs
1                          Fashion Sourcing Made Easy!
2  your way to find the healthiest and best price...
3       Online Video Discovery & Promotion Platform
4                                   On Demand Postman

                                        product_desc launch_date  \
0  Coffeetheapp is a mobile community of hiring m...  2014-07-01
1  WearMyTags.com solves the fashion/apparel indu...  2014-07-01
2  The Cherry Share is a mobile and web applicati...  2012-06-01
3  Vidinterest lets you discover and create priva...  2012-06-01
4  On-demand postman delivers packages locally.  ...  2014-06-01

             created_at  follower_count  quality company_size twitter  \
0  2014-04-29T20:07:33Z              48        4         1-10    True
1  2013-11-11T23:09:59Z              97        6         1-10    True
2  2013-07-17T11:31:00Z              36        5         1-10    True
3  2012-12-05T11:47:08Z              19        4         1-10    True
4  2014-03-05T18:58:10Z               5        4         1-10    True

  linkedin facebook website   blog  discount equity_basis  \
0     True     True    True  False       NaN       equity
1    False    False    True  False       NaN       equity
2    False     True    True   True       NaN       equity
3    False     True    True   True       NaN       equity
4    False    False    True   True       NaN       equity

   pre_money_valuation  raised_amount round_opened_at  raising_amount
0              3000000              0      2014-12-15          250000
1                  NaN              0      2014-12-14          750000
2              3000000          91000      2014-12-14          400000
3              1000000              0      2014-12-12          100000
4              1000000              0      2014-12-11          100000
```

In [207]:
```
ana.columns
```

Out[207]:
```
Index([u'id', u'name_x', u'high_concept', u'product_desc', u'launch_date', u'created_at', u'fol
```

In [155]:
```
#create precentage_raised column = raised_amount/raising_amount
```

In [303]:
```
ana['percentage_raised'] = 100*ana['raised_amount']/ana['raising_amount']
```

In [159]:
```
#response variable can be = percentage_raised or, for classifier, percentage_raised > 0;
# =0; > 100 (if we want three categories)
```

In [34]:
```
#now get column "days since round open" and column "days since launched"
```

2 First need to parse strings into datetime objects and then apply the delta operator for temporal difference between two datetime objects

3 use the pandas to_datetime; NaT is (not a time) for missing data

```
In [304]: launch_d=pd.to_datetime(ana['launch_date'])

In [305]: created = pd.to_datetime(ana['created_at'])

In [306]: d = pd.to_datetime(ana['round_opened_at'])

In [307]: d.head()

Out[307]: 0   2014-12-15
          1   2014-12-14
          2   2014-12-14
          3   2014-12-12
          4   2014-12-11
          Name: round_opened_at, dtype: datetime64[ns]

In [39]: #today's date

In [310]: from datetime import datetime
          tod = datetime.now()
          print tod

2014-12-17 13:26:35.653000

In [58]: #number of days between now and launch date

In [311]: days_since_launch = tod - launch_d
          days_since_launch.head()

In [ ]: #number of days since raising round opened

In [313]: days_since_round = tod - d
          days_since_round.head()

Out[313]: 0   2 days, 13:26:35.653000
          1   3 days, 13:26:35.653000
          2   3 days, 13:26:35.653000
          3   5 days, 13:26:35.653000
          4   6 days, 13:26:35.653000
          Name: round_opened_at, dtype: timedelta64[ns]

In [220]: days_since_created = tod - created

In [72]: #get the number of days since launch, created and round opened as numbers not timedelta object

In [314]: ana['days_launch'] = days_since_launch.astype('timedelta64[D]')
          ana['days_r'] = days_since_round.astype('timedelta64[D]')
          ana['days_created'] = days_since_created.astype('timedelta64[D]')

In [223]: #Create a temporary local copy of the data for analysis
```

```
In [315]: ana.to_pickle('ana_pickled')

In [316]: del ana

In [167]: #load pickle for analysis

In [2]: ana = pd.read_pickle('ana_pickled')

In [84]: #ANALYTICS

In [3]: ana.describe()

Out[3]:                    id  follower_count     quality    twitter   linkedin  \
        count     400.000000      400.000000  400.000000        400        400
        mean   361130.905000       23.810000    3.025000       0.46     0.1525
        std     99434.201323       73.550923    1.693086  0.4990216  0.3599551
        min      1447.000000        0.000000    1.000000      False      False
        25%    346012.500000        3.000000    2.000000          0          0
        50%    406998.000000        5.000000    3.000000          0          0
        75%    417614.750000       15.000000    4.000000          1          0
        max    438675.000000      863.000000    9.000000       True       True

                facebook website       blog   discount  pre_money_valuation  \
        count        400     400        400  53.000000         2.450000e+02
        mean      0.2475  0.9975     0.2325  17.849057         1.668349e+07
        std    0.4321001    0.05  0.4229551   8.244803         2.038386e+08
        min        False   False      False   0.000000         0.000000e+00
        25%            0       1          0  15.000000         2.500000e+05
        50%            0       1          0  20.000000         1.700000e+06
        75%            0       1          0  20.000000         4.500000e+06
        max         True    True       True  40.000000         3.192118e+09

                raised_amount  raising_amount  percentage_raised  days_launch  \
        count      400.000000    4.000000e+02         400.000000   128.000000
        mean     35829.377500    1.572787e+06           3.542742   482.140625
        std     228628.002403    1.126272e+07          13.780317   490.235613
        min          0.000000    1.000000e+01           0.000000  -196.000000
        25%          0.000000    8.000000e+04           0.000000   222.250000
        50%          0.000000    2.500000e+05           0.000000   350.000000
        75%          0.000000    6.000000e+05           0.000000   541.500000
        max    3760250.000000    1.600000e+08         110.595588  3272.000000

                   days_r  days_created
        count  400.000000    200.000000
        mean   165.277500    375.850000
        std     55.494772    287.841207
        min      2.000000    154.000000
        25%    166.750000    178.000000
        50%    187.000000    231.000000
        75%    202.000000    451.750000
        max    215.000000   1468.000000

In [319]: ana['percentage_raised'].describe(percentiles=[0.5,0.6,0.65,0.7,0.75,0.80,0.85,0.9,0.95,0.99,

Out[319]: count    400.000000
          mean       3.542742
```

```
std      13.780317
min       0.000000
50%       0.000000
60%       0.000000
65%       0.000000
70%       0.000000
75%       0.000000
80%       0.000000
85%       0.000000
90%       6.066667
95%      22.812500
99%      79.207000
100%    110.595588
max     110.595588
dtype: float64
```

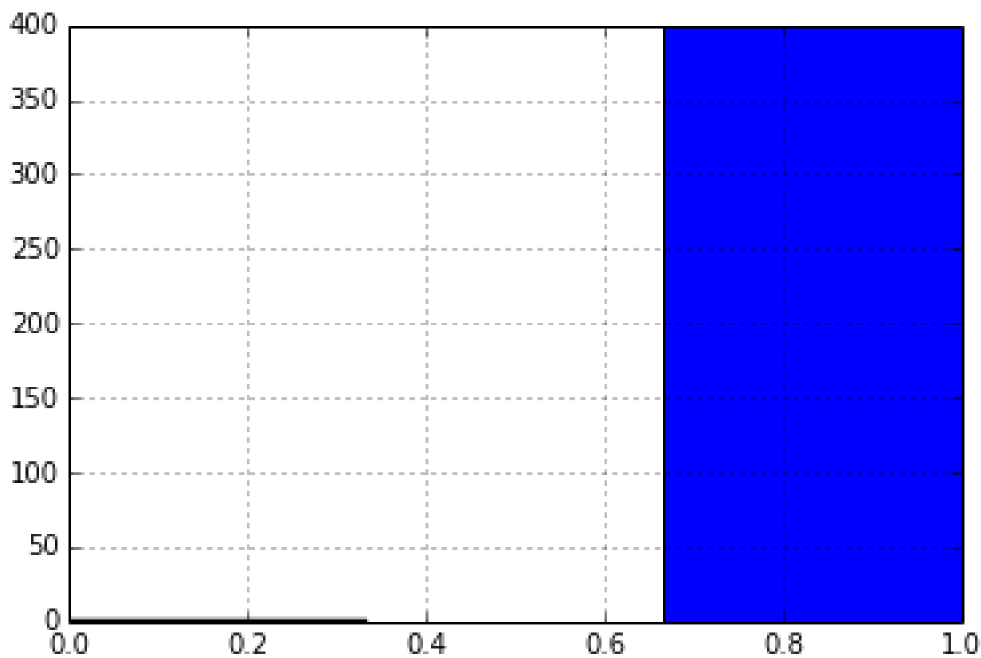
In [2]:
```
#it seems that majority did not raise anything, but some raised more than "raising_amount";
#interesting to see characteristics
#for those ones
```

In [320]:
```
pd.value_counts(ana['website'])
```

Out[320]:
```
True     399
False      1
dtype: int64
```

In [321]:
```
ana['website'].hist(bins = 3)
```

Out[321]:
```
<matplotlib.axes.AxesSubplot at 0x14a2f4e0>
```

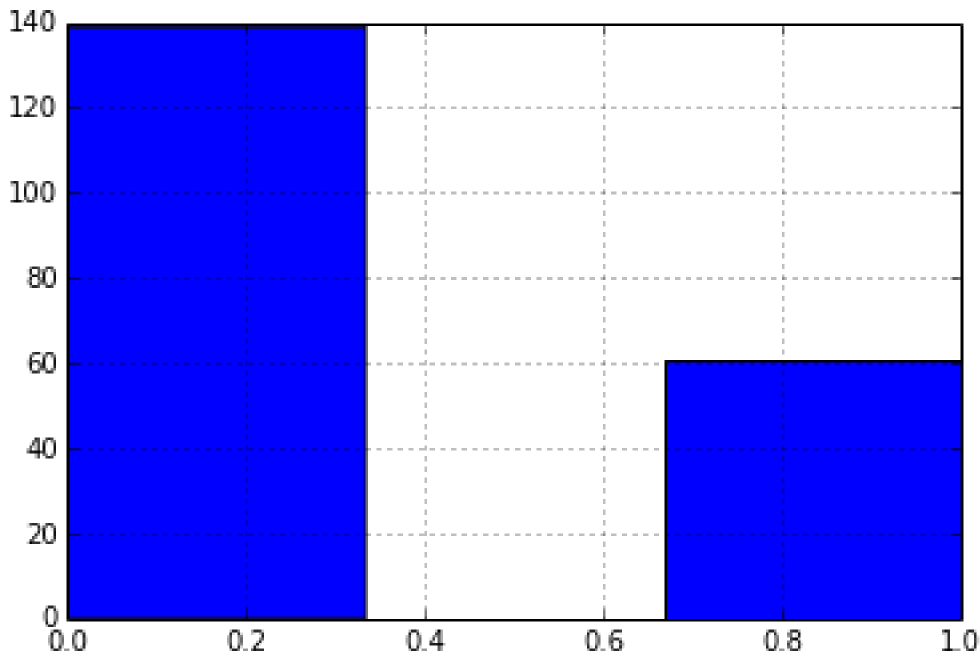


In [231]:
```
pd.value_counts(ana['blog'])
```

```
Out[231]: False    139
          True      61
          dtype: int64
```

```
In [232]: ana['blog'].hist(bins = 3)
```

```
Out[232]: <matplotlib.axes.AxesSubplot at 0x10cdc390>
```

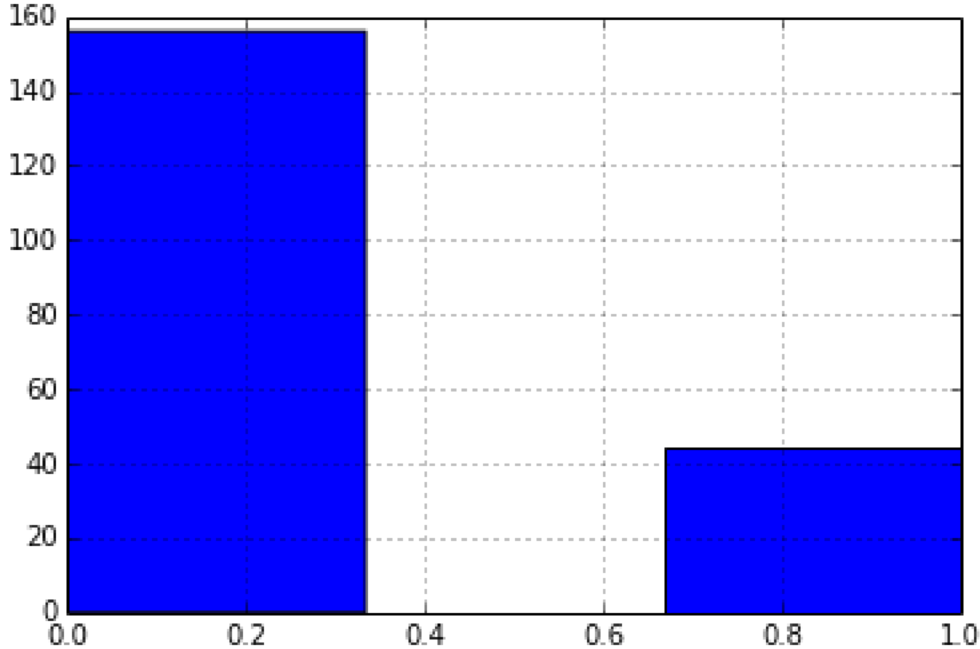



```
In [233]: pd.value_counts(ana['linkedin'])
```

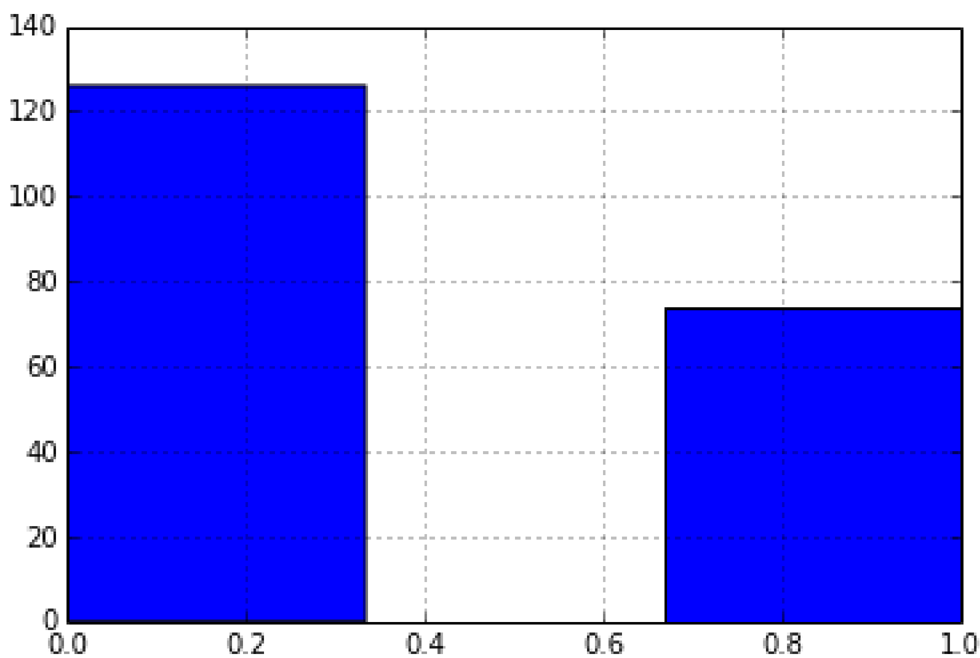
```
Out[233]: False    156
          True      44
          dtype: int64
```

```
In [234]: ana['linkedin'].hist(bins = 3)
```

```
Out[234]: <matplotlib.axes.AxesSubplot at 0x1118b208>
```




```
In [235]: pd.value_counts(ana['facebook'])

Out[235]: False    126
          True      74
          dtype: int64

In [236]: ana['facebook'].hist(bins = 3)

Out[236]: <matplotlib.axes.AxesSubplot at 0x128b2048>
```

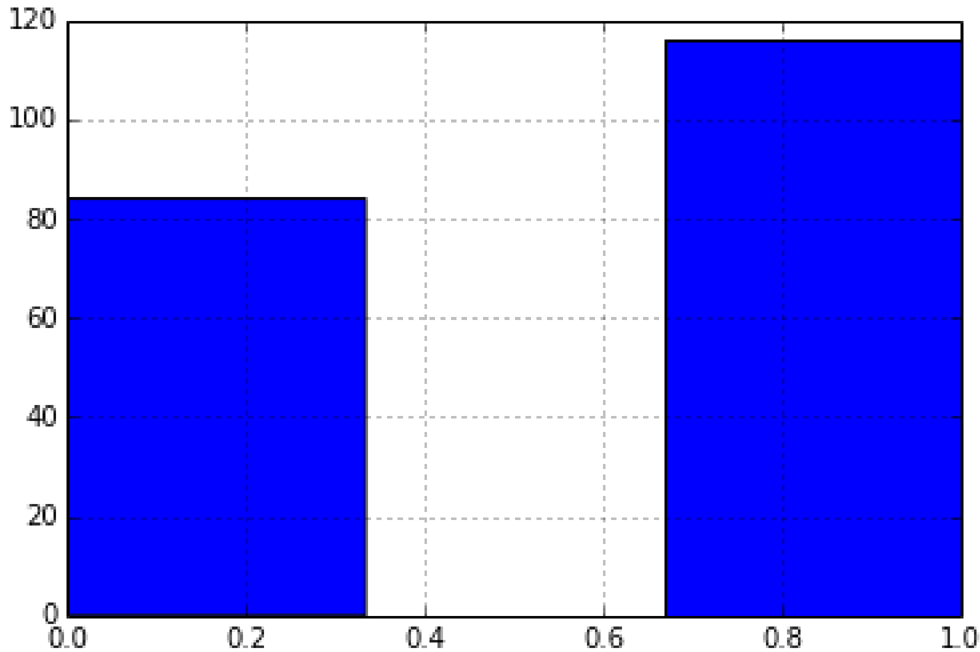


In [237]:
```
pd.value_counts(ana['twitter'])
```

Out[237]:
```
True     116
False     84
dtype: int64
```

In [238]:
```
ana['twitter'].hist(bins = 3)
```

Out[238]:
```
<matplotlib.axes.AxesSubplot at 0x129a29b0>
```

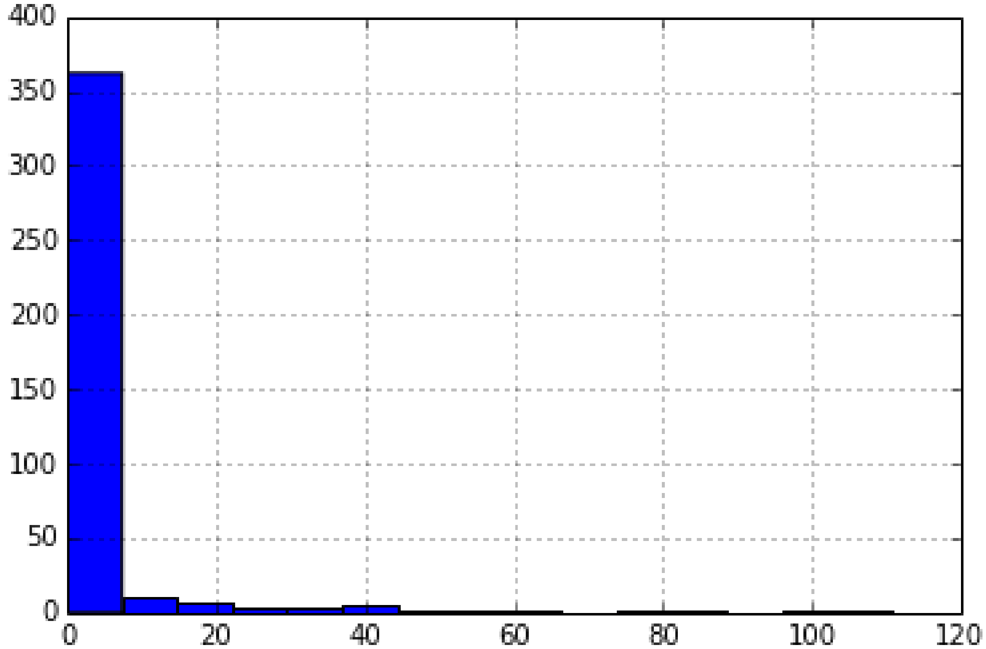


In [24]:
```
#Visualizations (more)
```

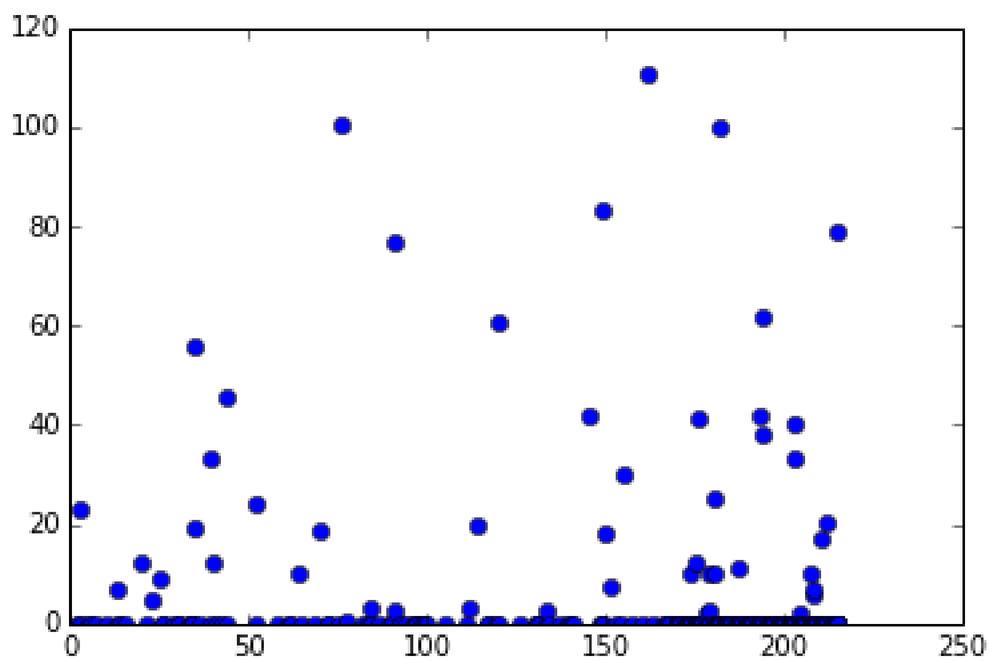
In [25]:
```
#Distribution of percentage raised
```

In [322]:
```
ana['percentage_raised'].hist(bins=15)
```

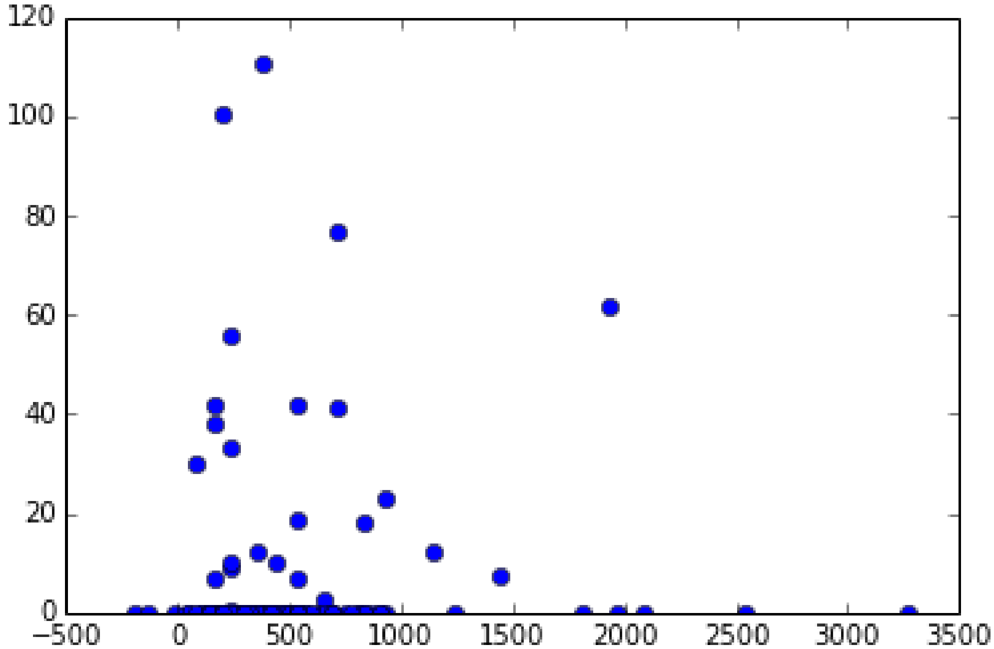
Out[322]:
```
<matplotlib.axes.AxesSubplot at 0x14f364e0>
```



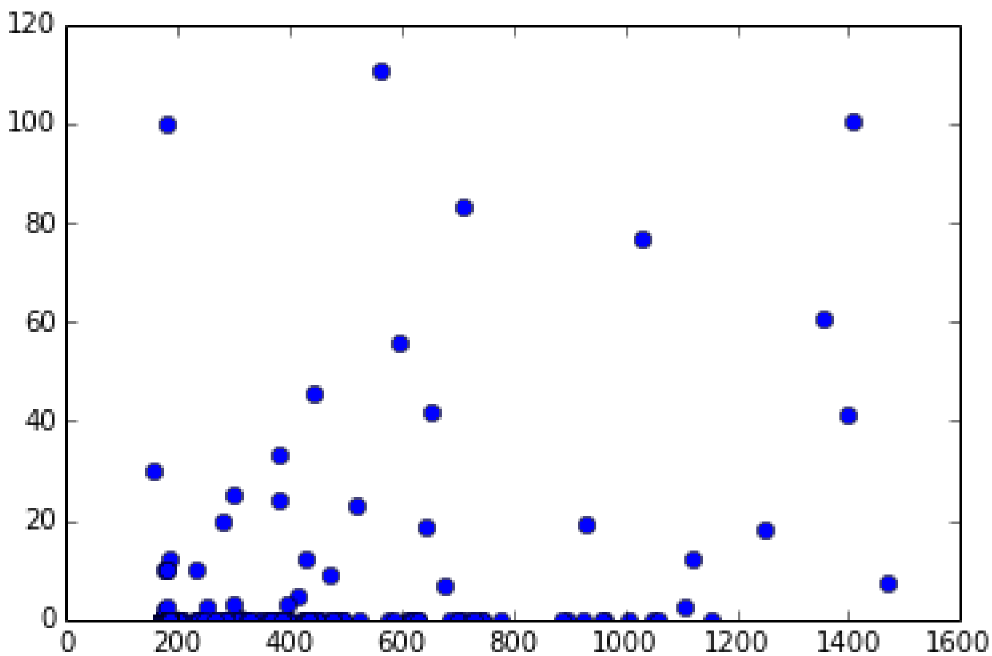

```
In [ ]: #percentage raised vs number of days since round open

In [323]: plt.plot(ana['days_r'],ana['percentage_raised'],'bo')

Out[323]: [<matplotlib.lines.Line2D at 0x15394dd8>]
```



```
In [ ]: #Plot percentage raised( y axis) vs number of days since company launch (x axis)

In [324]: plt.plot(ana['days_launch'],ana['percentage_raised'],'bo')

Out[324]: [<matplotlib.lines.Line2D at 0x153b9860>]
```



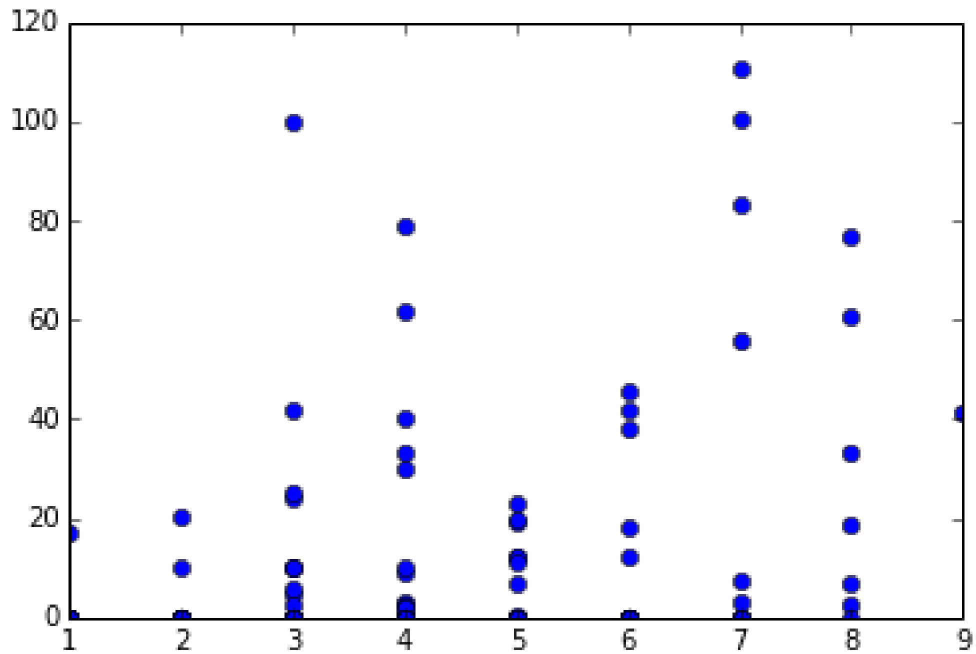

```
In [325]: plt.plot(ana['days_created'],ana['percentage_raised'],'bo')

Out[325]: [<matplotlib.lines.Line2D at 0x156eb748>]
```



```
In [99]: #percentage raised vs quality of the company (variable specific to Angellist site)
```

```
In [326]: plt.plot(ana['quality'],ana['percentage_raised'],'bo')
```

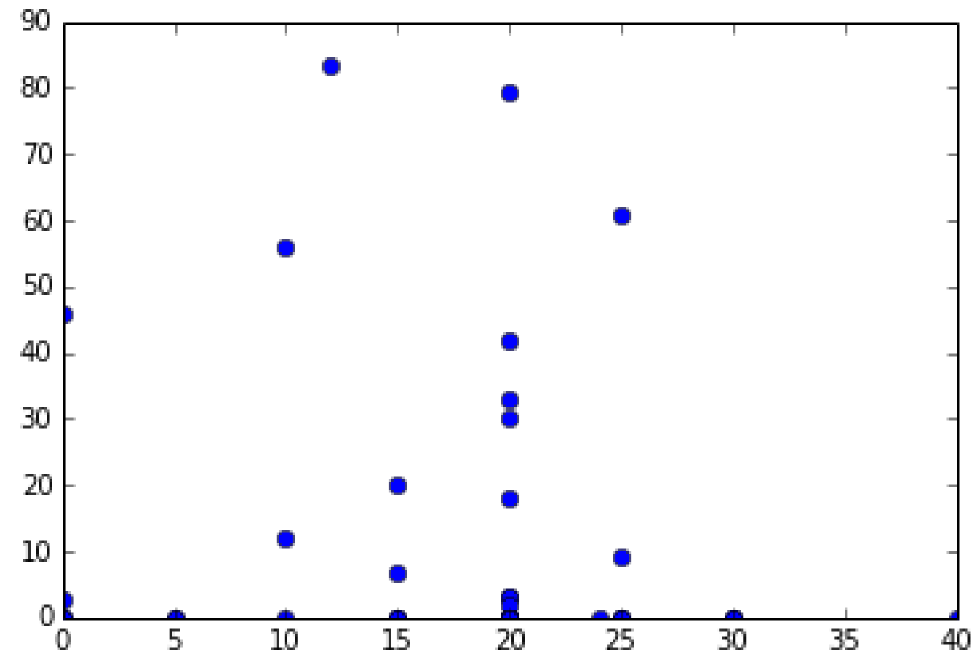
```
Out[326]: [<matplotlib.lines.Line2D at 0x158a3630>]
```




```
In [80]: #percentage raised vs discount of the company (variable specific to Angellist site)
```

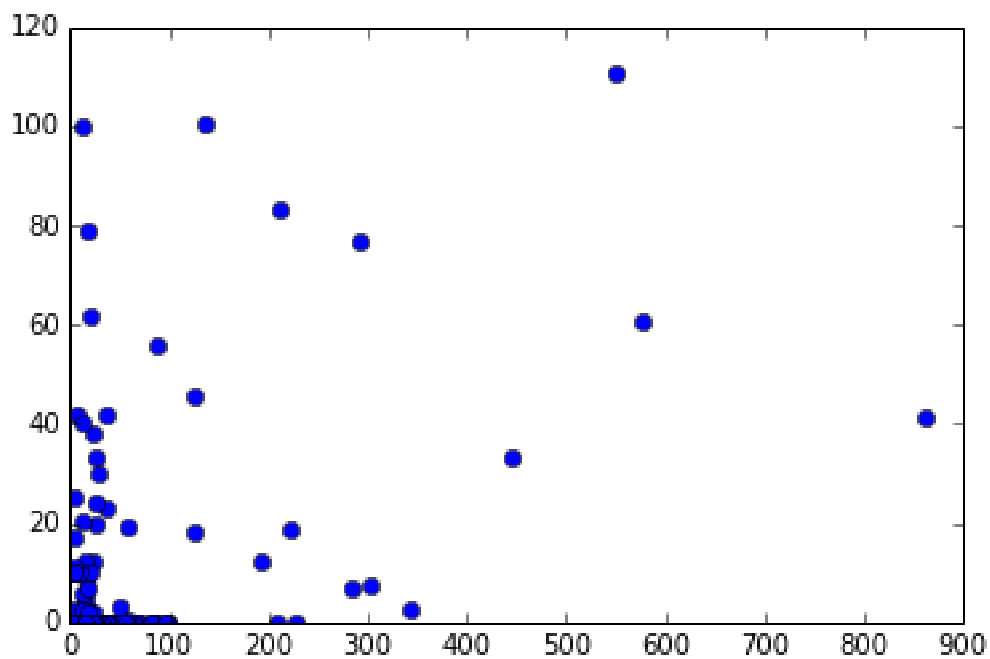
```
In [327]: plt.plot(ana['discount'],ana['percentage_raised'],'bo')
```

```
Out[327]: [<matplotlib.lines.Line2D at 0x158ce518>]
```




```
In [328]: plt.plot(ana['follower_count'],ana['percentage_raised'],'bo')
```

```
Out[328]: [<matplotlib.lines.Line2D at 0x15c6e898>]
```




```
In [329]: pre_m = ana['pre_money_valuation']/1000
```

In [330]: pre_m.describe()

```
Out[330]: count        245.000000
          mean       16683.489216
          std       203838.602312
          min            0.000000
          25%          250.000000
          50%         1700.000000
          75%         4500.000000
          max      3192118.227000
          dtype: float64
```

In [335]: p1 = ana['pre_money_valuation'] < 3000000

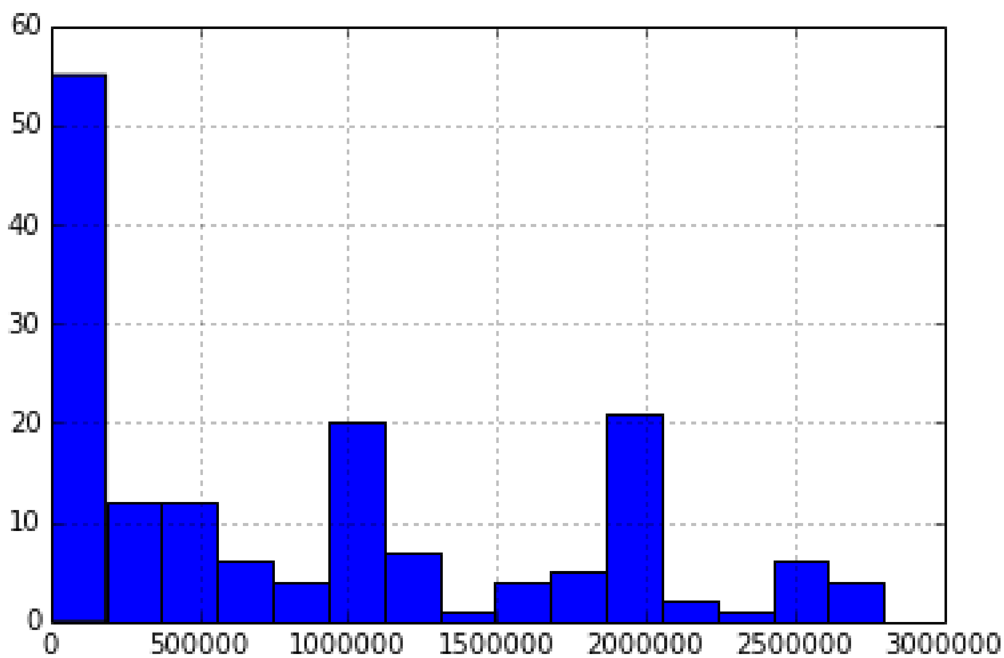
In [336]: pre_m_lower = ana[p1]['pre_money_valuation']

In [337]: pre_m_lower.describe()

```
Out[337]: count        160.00000
          mean      855041.44375
          std       847131.43358
          min            0.00000
          25%        50000.00000
          50%       600000.00000
          75%      1500000.00000
          max      2800000.00000
          dtype: float64
```

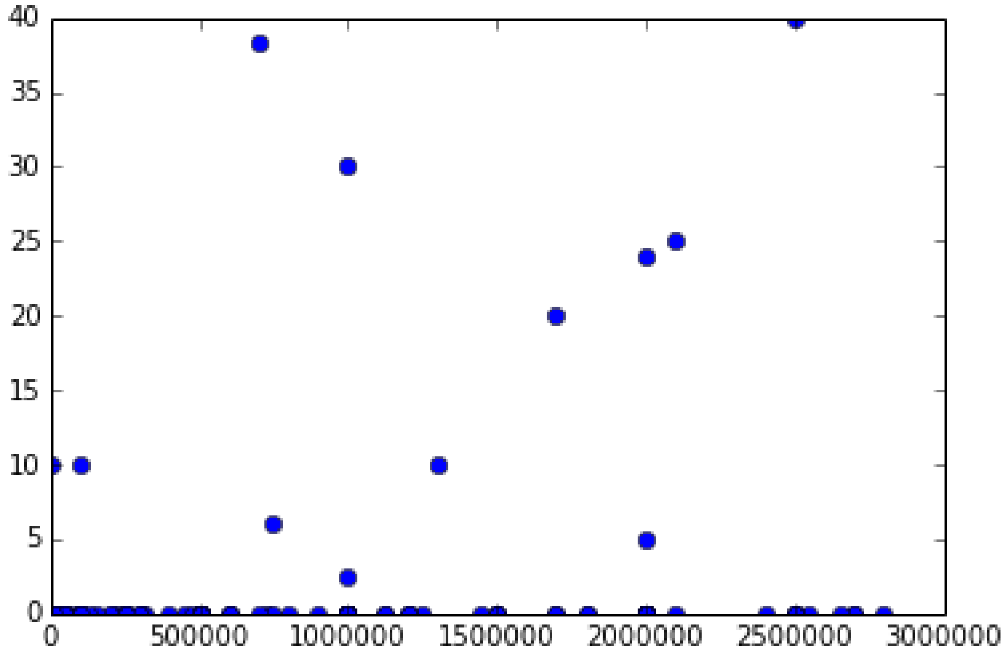
In [338]: pre_m_lower.hist(bins=15)

Out[338]: <matplotlib.axes.AxesSubplot at 0x15f867b8>



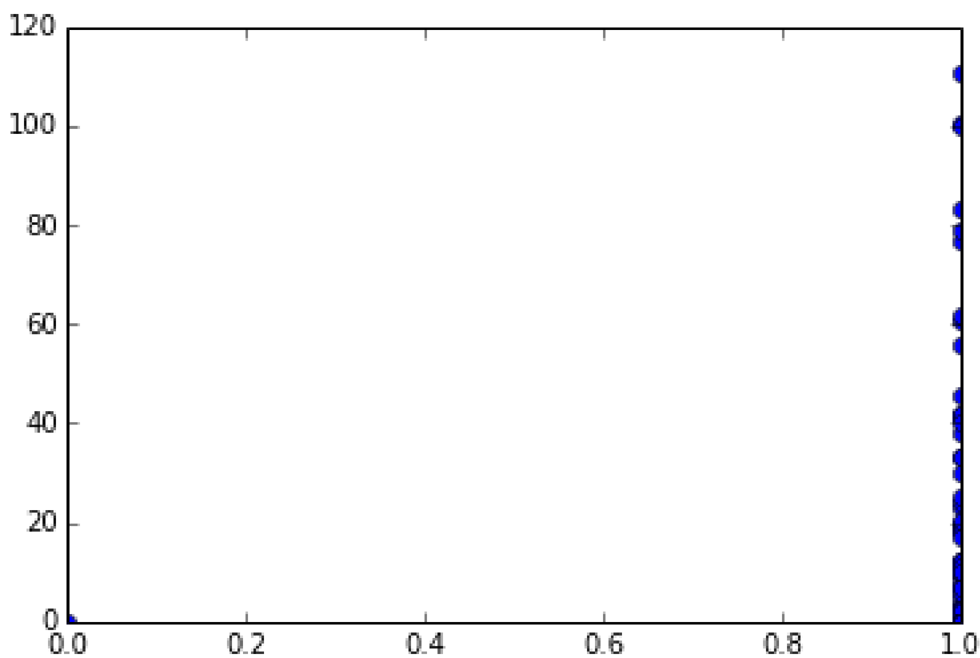
```
In [339]: plt.plot(ana[p1]['pre_money_valuation'],ana[p1]['percentage_raised'],'bo')
```

```
Out[339]: [<matplotlib.lines.Line2D at 0x163a86d8>]
```



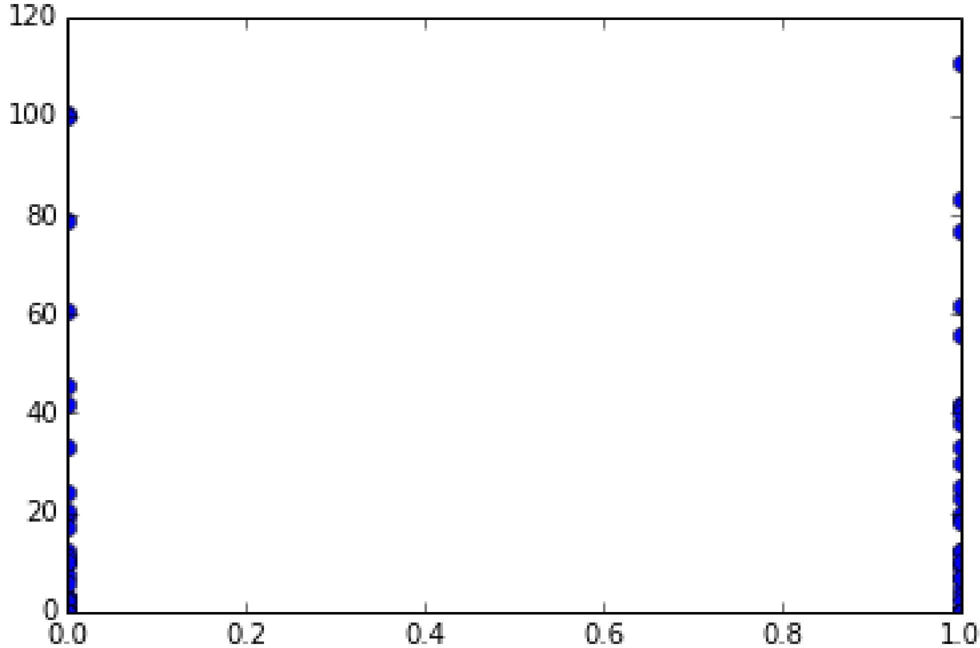

```
In [340]: plt.plot(ana['website'],ana['percentage_raised'],'bo')
```

```
Out[340]: [<matplotlib.lines.Line2D at 0x16696518>]
```



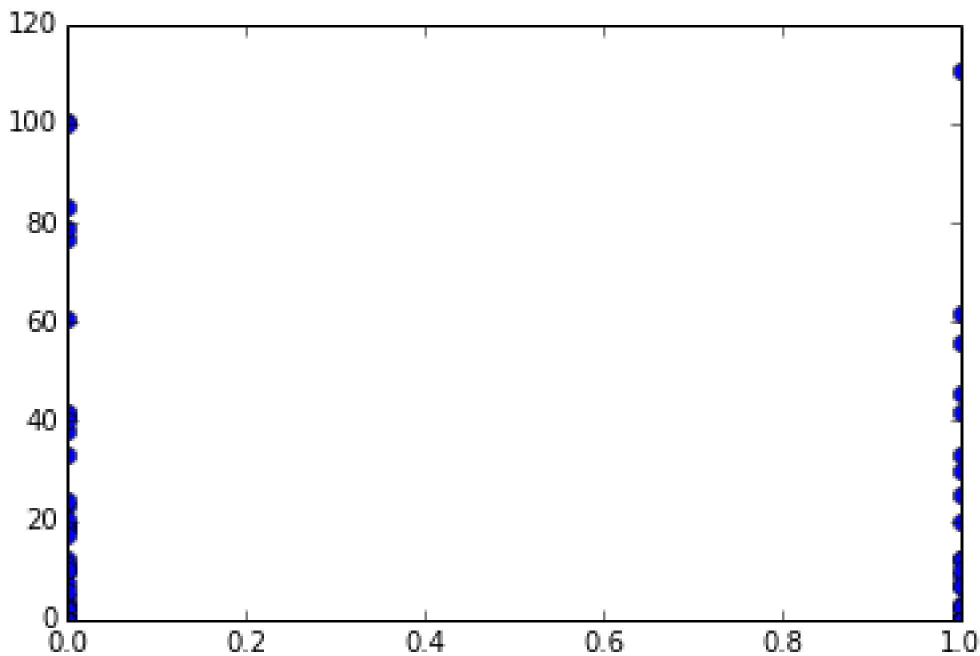
In [341]: plt.plot(ana['facebook'],ana['percentage_raised'],'bo')

Out[341]: [<matplotlib.lines.Line2D at 0x166bdf28>]



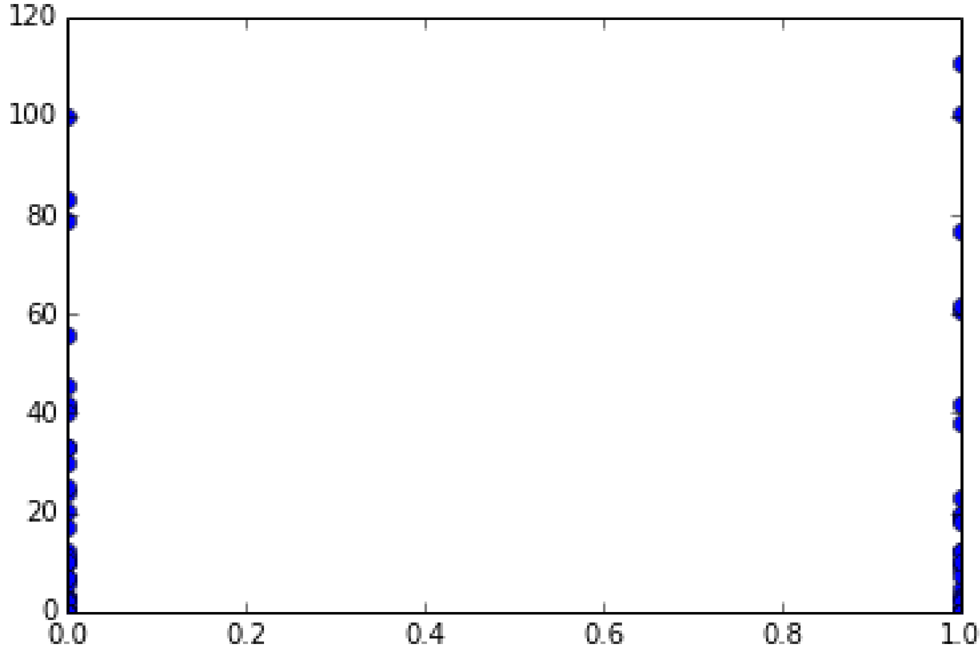
In [342]: plt.plot(ana['linkedin'],ana['percentage_raised'],'bo')

Out[342]: [<matplotlib.lines.Line2D at 0x169b4978>]



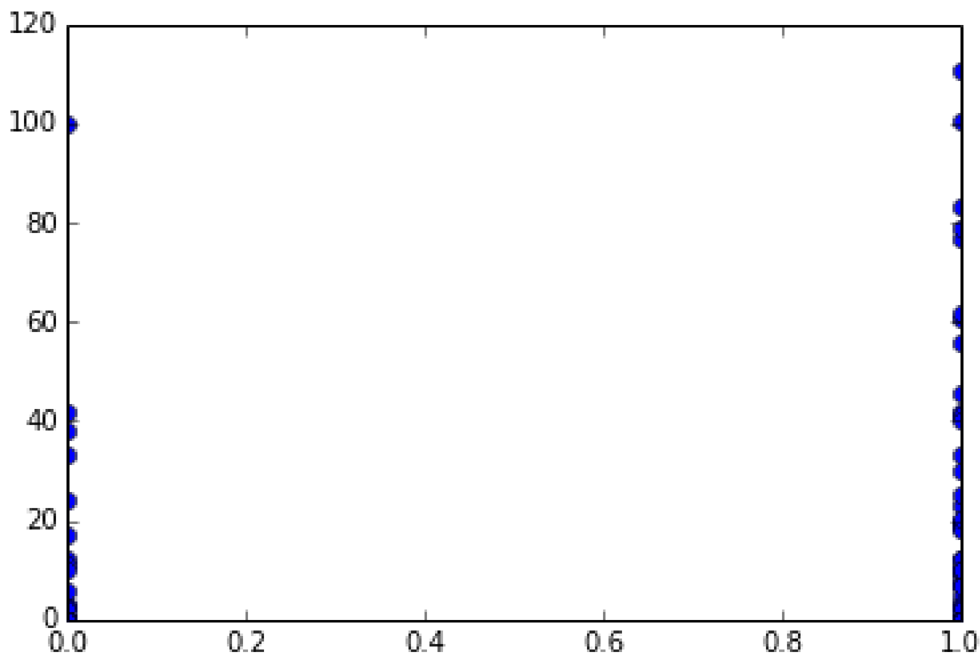
```
In [344]: plt.plot(ana['blog'],ana['percentage_raised'],'bo')
```

```
Out[344]: [<matplotlib.lines.Line2D at 0x16c7fda0>]
```




```
In [345]: plt.plot(ana['twitter'],ana['percentage_raised'],'bo')
```

```
Out[345]: [<matplotlib.lines.Line2D at 0x16f827f0>]
```



In [109]: #Create the boolean variable raise = 0 if the company raised 0% and raise = 1 if the company

In [346]: target = ana['percentage_raised'] > 0

In [114]: #Implement a logistic regression classification algorithm to see how well we can use
#the following features to predict if the company will raise something or nothing

In [115]: #Use Scikit-Learn Python libraries for model implementation

In [347]:
```
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
```

In [117]:
```
#We know the true classification for our data; will first create another dataset with the
#features of interest
#and then take a train and test set
```

In [348]:
```
features = ['website', 'blog' , 'linkedin', 'facebook', 'twitter','days_launch','days_created
            'days_r','follower_count','quality']
```

In [349]: `data = ana[features]`

In [350]: `del ana`

In [124]: `#Create test and train set`

In [351]: `from sklearn.cross_validation import train_test_split`

In [352]:
```
X_train, X_test, y_train, y_test = train_test_split(data, target, test_size=0.25,
                                                    random_state=33)
```

In [353]: `del data`

In [354]: `del target`

In [355]: `X_train.shape, y_train.shape`

Out[355]: ((300L, 10L), (300L,))

In [356]: `X_test.shape, y_test.shape`

Out[356]: ((100L, 10L), (100L,))

In [135]: `#fit classification model with training data; first deal with missing values`

In [357]:
```
from sklearn.preprocessing import Imputer
imp = Imputer(missing_values='NaN', strategy='mean', axis=0)
```

In [358]: `imp.fit(X_train)`

Out[358]: Imputer(axis=0, copy=True, missing_values='NaN', strategy='mean', verbose=0)

In [359]: `X_train_imp = imp.transform(X_train)`

In [360]: `del X_train`

In [361]:
```
model = LogisticRegression()
m = model.fit(X_train_imp, y_train)
```

```
In [362]: m

Out[362]: LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                    intercept_scaling=1, penalty='l2', random_state=None, tol=0.0001)

In [363]: m.coef_

Out[363]: array([[ -1.18947911e+00,   1.71814396e-01,   5.61057452e-01,
                    1.02474909e-01,   3.86547994e-01,   1.83987118e-04,
                   -1.65509435e-03,  -6.27958267e-03,   1.07225575e-02,
                    3.36200353e-01]])

In [364]: exp(m.coef_) #exponential of coefficients is odds of increase in probability
          # of raising due to increase in one of the features

Out[364]: array([[ 0.30437977,  1.18745742,  1.75252473,  1.1079095 ,  1.47189104,
                   1.000184  ,  0.99834627,  0.99374009,  1.01078025,  1.39961942]])

In [152]: #Can look at the relative importance of features through their odds ratios (can eyeball)
          #features = ['website', 'blog' , 'linkedin', 'facebook', 'twitter','days_launch','days_create
          # 'days_r','follower_count','quality']

In [365]: # make predictions using train data
          predicted = m.predict(X_train_imp)

In [366]: # summarize the fit of the model using train data
          print(metrics.classification_report(y_train, predicted))
          print(metrics.confusion_matrix(y_train, predicted))

precision    recall  f1-score   support

      False       0.90      0.98      0.94       261
       True       0.62      0.26      0.36        39

avg / total       0.86      0.88      0.86       300

[[255   6]
 [ 29  10]]

In [367]: # imput test data; using imputation means from train data
          X_test_imp = imp.transform(X_test)

In [368]: del X_test

In [369]: # make predictions using train data
          predicted = m.predict(X_test_imp)

In [370]: # summarize the fit of the model using test data
          print(metrics.classification_report(y_test, predicted))

precision    recall  f1-score   support

      False       0.92      0.98      0.95        89
       True       0.60      0.27      0.37        11

avg / total       0.88      0.90      0.88       100

In [371]: print(metrics.confusion_matrix(y_test, predicted))
```

```
[[87  2]
 [ 8  3]]
```

```
In [372]: metrics.accuracy_score(y_test, predicted)
```

```
Out[372]: 0.90000000000000002
```

```
In [ ]:
```