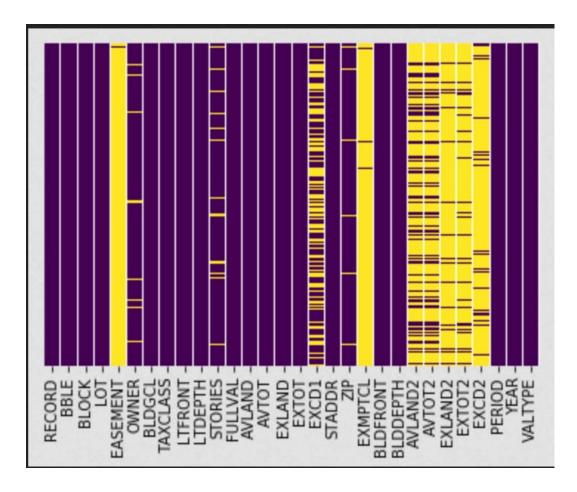
To: Professor Stephen Coggeshall

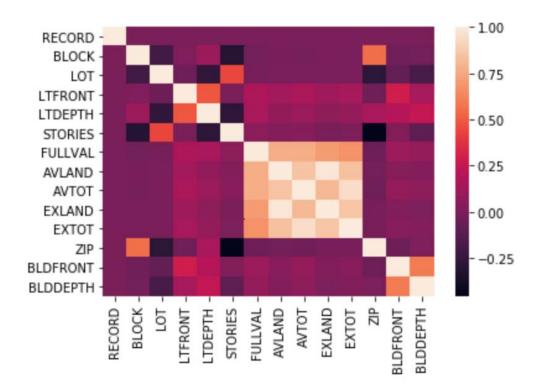
From: Alok Abhishek Date: 01/24/2018

Subject: DSO 562: Fraud Analytics

Before starting data analysis and visualization I created a heatmap for missing values. I then removed the columns from deeper analysis because so much data is missing that interpreting few entries does not help me in looking at the bigger picture. (I've added python code for data analysis and visualization at the end the assignment)

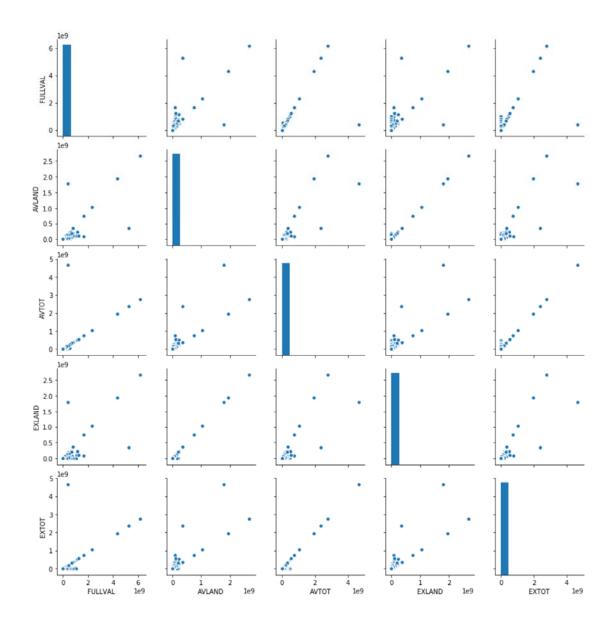


I then created heat map of correlation in between different variables to identify trends in data. I could use this relationship within data to identify outliers and potential fraud candidates.

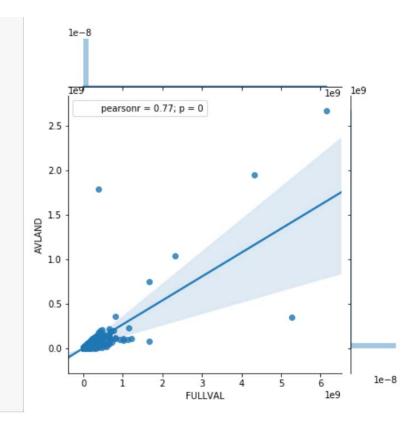


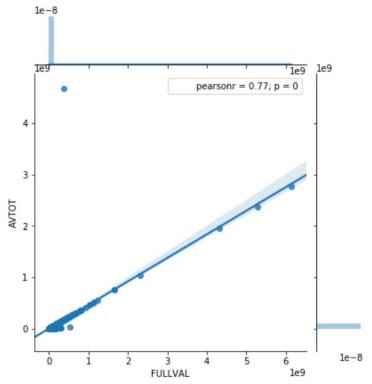
From the correlation plot we can see that there is high correlation in between Full Value, Average Land, Average Total, Ex Land, and Ex Total. I did a pair plot for these variables to identify the outliers.

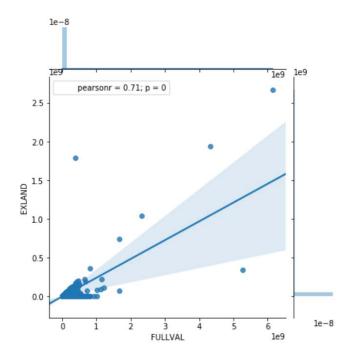
Most of the variable looks well aligned across the 45 degree slope with few outliers.

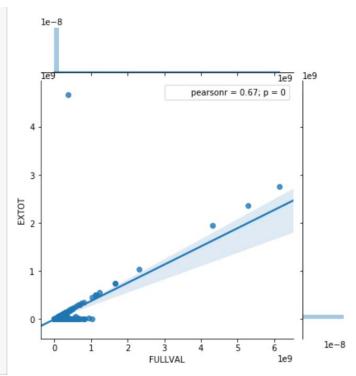


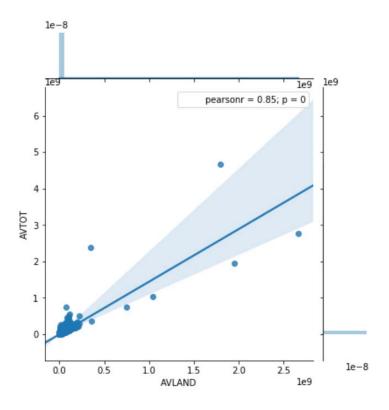
Following is more in depth look at some plots which has out of pattern data points. These data points which resides outside the shaded regression region are good candidate to look at for fraud. Some of these will have valid reason and some of them could be data entry error and some may be fraudulent data.

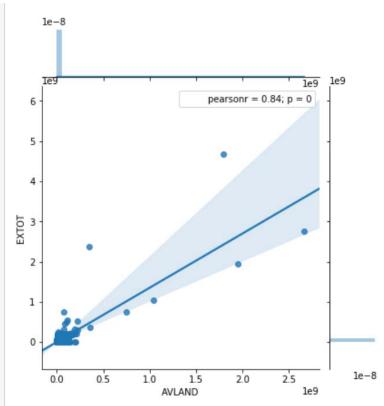












While looking at the stories of buildings I noticed that there are several buildings with # of stories in decimals. This looks odd.

```
NYC Property data.groupby('STORIES').count()['RECORD']
STORIES
1.0
           93606
1.1
               3
1.2
              33
1.3
                3
1.4
                2
1.5
           24354
1.6
            8816
1.7
            5051
1.8
              21
1.9
              10
2.0
          403318
2.1
               1
2.2
              40
2.3
              19
2.4
               2
2.5
           81304
2.6
             226
2.7
           13543
2.8
                3
2.9
               1
3.0
          128493
3.2
              14
3.3
               5
3.5
            1188
3.6
              11
3.7
             251
4.0
           38337
4.2
               1
4.5
             290
4.7
              10
```

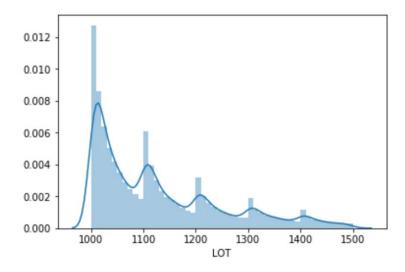
I also looked at lot front, lot depth, building front, and building depth. I noticed that there are a lot of properties with value zero for these fields which looks odd because how can building have 0 lot front or 0 lot depth.

```
NYC Property data 2.groupby('LTFRONT').count()['RECORD']
LTFRONT
        168867
1
           819
2
           750
NYC Property data 2.groupby('LTDEPTH').count()['RECORD']
LTDEPTH
0
        169888
1
           126
2
             79
             01
NYC Property data 2.groupby('BLDFRONT').count()['RECORD']
BLDFRONT
0
         224661
1
             70
2
             20
3
             14
NYC Property data 2.groupby('BLDDEPTH').count()['RECORD']
BLDDEPTH
0
        224699
1
            52
2
             9
3
            90
            60
```

Looking at the lot size in depth it seems like lot depth increases in increment of 100s.

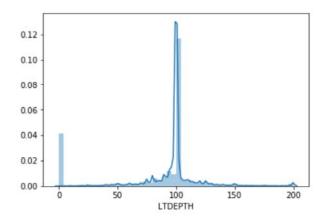
```
tmp = NYC_Property_data[NYC_Property_data['LOT']<=1500]
tmp = tmp[tmp['LOT']>=1000]
sbrn.distplot(tmp['LOT'], bins=50)
```

<matplotlib.axes. subplots.AxesSubplot at 0x1766618e470>



Looking at the lot depth it seems interesting that most of the lot depths are approximately 100.

```
sbrn.distplot(NYC_Property_data_2[NYC_Property_data_2['LTDEPTH']<=200]['LTDEPTH'],bins=50)
<matplotlib.axes._subplots.AxesSubplot at 0x2108cd91940>
```



```
In [2]: import numpy as np
import pandas as pd
import sklearn as sk
import seaborn as sbrn
import matplotlib.pyplot as plt
%matplotlib inline
```

In [3]: NYC_Property_data = pd.read_csv('NY property 1 million.csv')

In [4]: NYC_Property_data.describe()

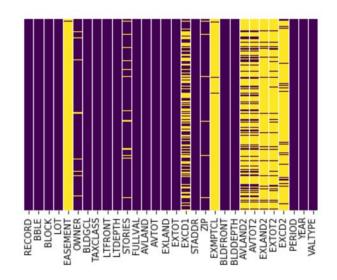
Out[4]:

	RECORD	BLOCK	LOT	LTFRONT	LTDEPTH	STORIES	F
count	1.048575e+06	1.048575e+06	1.048575e+06	1.048575e+06	1.048575e+06	996433.000000	1.048
mean	5.242880e+05	4.708867e+03	3.700924e+02	3.617425e+01	8.827643e+01	5.063363	8.804
std	3.026977e+05	3.699547e+03	8.605382e+02	7.373356e+01	7.547885e+01	8.431372	1.170
min	1.000000e+00	1.000000e+00	1.000000e+00	0.000000e+00	0.000000e+00	1.000000	0.000
25%	2.621445e+05	1.534000e+03	2.300000e+01	1.900000e+01	8.000000e+01	2.000000	3.030
50%	5.242880e+05	3.944000e+03	4.900000e+01	2.500000e+01	1.000000e+02	2.000000	4.460
75%	7.864315e+05	6.797000e+03	1.460000e+02	4.000000e+01	1.000000e+02	3.000000	6.190
max	1.048575e+06	1.635000e+04	9.978000e+03	9.999000e+03	9.999000e+03	119.000000	6.150

```
In [5]: NYC_Property_data.info()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 1048575 entries, 0 to 1048574
        Data columns (total 30 columns):
               1048575 non-null int64
        RECORD
                   1048575 non-null object
        BBLE
        BLOCK
                   1048575 non-null int64
                   1048575 non-null int64
        EASEMENT
                   4043 non-null object
        OWNER
                   1017492 non-null object
        BLDGCL
                   1048575 non-null object
        TAXCLASS
                   1048575 non-null object
        LTFRONT
                   1048575 non-null int64
                   1048575 non-null int64
        LTDEPTH
                   996433 non-null float64
        STORIES
        FULLVAL
                   1048575 non-null int64
        AVLAND
                   1048575 non-null int64
                   1048575 non-null int64
        AVTOT
        EXLAND
                   1048575 non-null int64
        EXTOT
                   1048575 non-null int64
        EXCD1
                   622642 non-null float64
        STADDR
                   1047934 non-null object
        ZIP
                   1022219 non-null float64
        EXMPTCL
                   14992 non-null object
        BLDFRONT
                   1048575 non-null int64
        BLDDEPTH
                   1048575 non-null int64
        AVLAND2
                   280966 non-null float64
        AVTOT2
                   280972 non-null float64
        EXLAND2
                   86675 non-null float64
                   129933 non-null float64
        EXTOT2
        EXCD2
                   90941 non-null float64
        PERIOD
                   1048575 non-null object
                   1048575 non-null object
        VALTYPE 1048575 non-null object
        dtypes: float64(8), int64(12), object(10)
        memory usage: 240.0+ MB
```

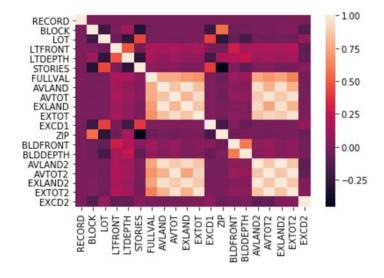
In [6]: sbrn.heatmap(NYC_Property_data.isnull(),yticklabels=False,cbar=False,cmap='viridis'
)

Out[6]: <matplotlib.axes._subplots.AxesSubplot at 0x21090ac4cf8>



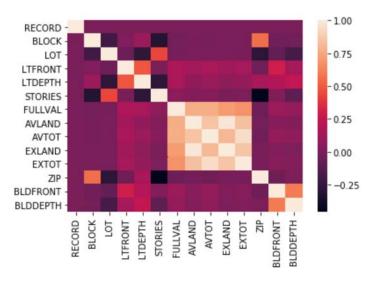
```
In [10]: sbrn.heatmap(NYC_Property_data.corr(),annot=False)
```

Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x17613a56f98>



In [8]: sbrn.heatmap(NYC_Property_data_2.corr(),annot=False)

Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x2108d939390>

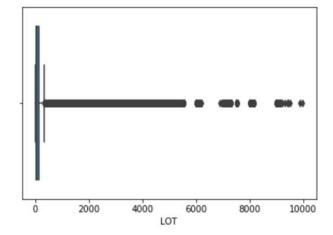


In [41]: NYC_Property_data['LOT'].describe()

```
Out[41]: count
                   1.048575e+06
                   3.700924e+02
         mean
                   8.605382e+02
         std
                   1.000000e+00
         min
                   2.300000e+01
         25%
         50%
                   4.900000e+01
         75%
                   1.460000e+02
                   9.978000e+03
         max
         Name: LOT, dtype: float64
```

In [42]: sbrn.boxplot(NYC_Property_data['LOT'])

Out[42]: <matplotlib.axes._subplots.AxesSubplot at 0x176665884e0>



In [36]: NYC_Property_data_2.groupby('LOT').count()['RECORD']

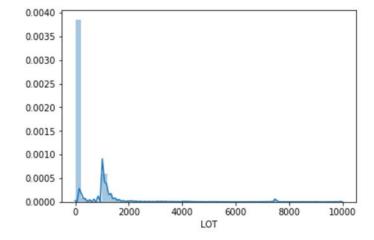
Out[36]:	LOT				
046[30].	1	23570			
	2	6552			
	3	9503			
	4	8993			
	5	10433			
	6	11418			
	7	11070			
	8	10673			
	9	10872			
	10 11	10876 10773			
	12	11894			
	13	11086			
	14	11864			
	15	11904			
	16	11810			
	17	11728			
	18	11763			
	19	11408			
	20	12045			
	21 22	11593 11462			
	23	11462			
	24	11392			
	25	11692			
	26	11390			
	27	11107			
	28	11170			
	29	11149			
	30	11354			
	9102	2			
	9102	1			
	9104	1			
	9105	1			
	9106	1			
	9107	1			
	9108	1			
	9109	1			
	9110	2			
	9111	1			
	9112 9113	1 1			
	9114	1			
	9115	1			
	9116	1			
	9117	1			
	9121	3			
	9130	1			
	9132	1			
	9134	1			
	9150 9172	1 1			
	9220	1			
	9300	1			
	9401	1			
	9421	1			
	9450	1			
	9502	1			
	9878	1			
	9978	1	_		•
	Name:	RECORD,	Length:	6366,	dtype:

6 of 29 1/24/2018, 11:46 PM

int64

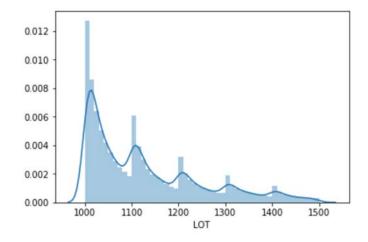
```
In [38]: sbrn.distplot(NYC_Property_data['LOT'],bins=50)
```

Out[38]: <matplotlib.axes._subplots.AxesSubplot at 0x17665f71a20>



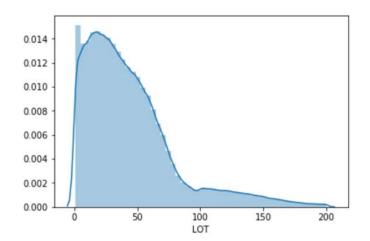
```
In [40]: tmp = NYC_Property_data[NYC_Property_data['LOT']<=1500]
    tmp = tmp[tmp['LOT']>=1000]
    sbrn.distplot(tmp['LOT'],bins=50)
```

Out[40]: <matplotlib.axes._subplots.AxesSubplot at 0x1766618e470>



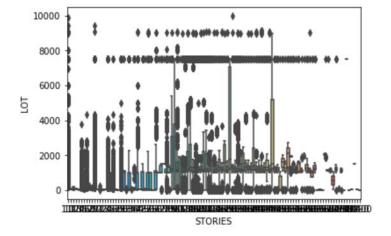
In [37]: sbrn.distplot(NYC_Property_data[NYC_Property_data['LOT']<=200]['LOT'],bins=50,kde=T
rue)</pre>

Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x17665fff438>



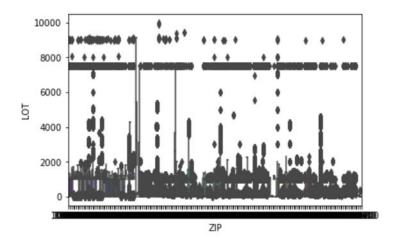
```
In [43]: sbrn.boxplot(x='STORIES',y='LOT',data=NYC_Property_data,palette='rainbow')
```

Out[43]: <matplotlib.axes._subplots.AxesSubplot at 0x17666632400>



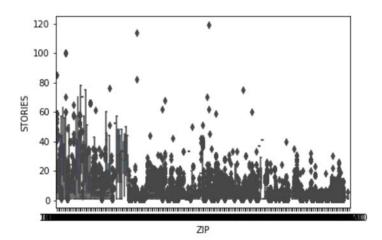
In [44]: sbrn.boxplot(x='ZIP',y='LOT',data=NYC_Property_data,palette='rainbow')

Out[44]: <matplotlib.axes._subplots.AxesSubplot at 0x17615541320>



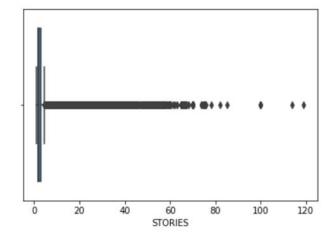
In [45]: sbrn.boxplot(x='ZIP',y='STORIES',data=NYC_Property_data,palette='rainbow')

Out[45]: <matplotlib.axes._subplots.AxesSubplot at 0x176157eaba8>



```
In [50]: NYC_Property_data['STORIES'].describe()
Out[50]: count 996433.000000
        mean
                      5.063363
                      8.431372
        std
                     1.000000
        min
        25%
                     2.000000
        50%
                     2.000000
        75%
                     3.000000
                   119.000000
        max
        Name: STORIES, dtype: float64
In [51]: sbrn.boxplot(NYC_Property_data['STORIES'])
```

Out[51]: <matplotlib.axes._subplots.AxesSubplot at 0x1761bdeb4e0>

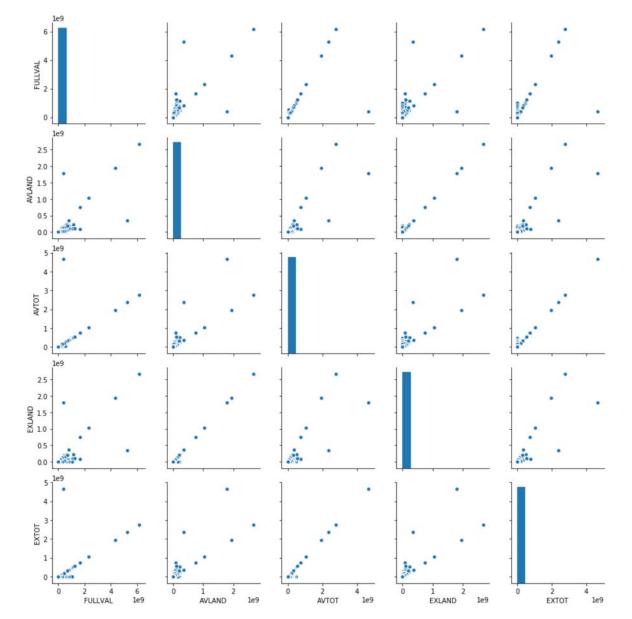


9 of 29

In [58]: NYC_Property_data.groupby('STORIES').count()['RECORD']

Out[58]:	STORIE	ls.				
	1.0	9360	6			
	1.1		3			
	1.2	3	3			
	1.3		3			
	1.4		2			
	1.5	2435				
	1.6	881				
	1.7	505				
	1.8		1			
	1.9	40331	.0 Q			
	2.1	40331	1			
	2.2	4	.0			
	2.3		.9			
	2.4		2			
	2.5	8130	4			
	2.6	22	6			
	2.7	1354	:3			
	2.8		3			
	2.9		1			
	3.0	12849				
	3.2	1	.4			
	3.3 3.5	118	5			
	3.6		.1			
	3.7	25				
	4.0	3833				
	4.2		1			
	4.5	29	0			
	4.7	1	.0			
	48.0	86				
	49.0 50.0	47 121				
	51.0	10				
	52.0	34				
	53.0		4			
	54.0	36				
	55.0	38	0			
	56.0	22	6			
	57.0	144	:5			
	58.0	25				
	59.0		.2			
	60.0	56				
	61.0		1			
	62.0 63.0		2			
	65.0	7	2			
	66.0		6			
	67.0	24				
	68.0		2			
	70.0	84	.9			
	74.0		6			
	75.0	3	1			
	76.0		1			
	78.0		1			
	82.0		1			
	85.0 100.0		1 5			
	114.0		1			
	114.0		1			
	Name:	RECORD,		111.	dtvpe:	int64
		,		,	~~1PC.	

Out[9]: <seaborn.axisgrid.PairGrid at 0x2108c0d6438>

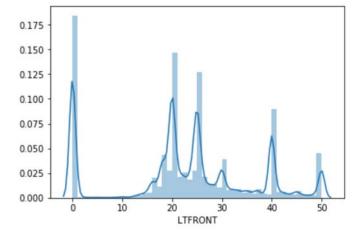


In [14]: NYC_Property_data_2.groupby('LTFRONT').count()['RECORD']

Out[14]:	LTFRONT 0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29	168867 819 750 304 269 505 231 270 363 403 1139 294 1172 2327 4027 4864 18359 10372 40188 25185 134447 19319 23304 16801 25180 116301 19415 12485 12963 9249
	4129 4152 4171 4300 4318 4507 4644 4646 4775 4824 4910 4989 5262 5370 5380 5400 5425 5878 6078 6317 6500 7536 7653 8000 8715 8744 8821 9170 9742 9999 Name: F	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

Name: RECORD, Length: 1277, dtype: int64

Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x2108cc56ba8>



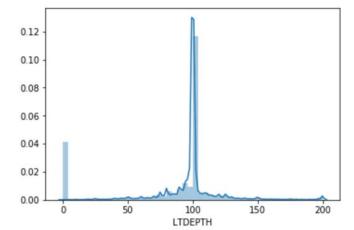
In [16]: NYC_Property_data_2.groupby('LTDEPTH').count()['RECORD']

0	T	**
Out[16]:	LTDEPT	
	0	169888
	1	126
	2	
		79
	3	81
	4	85
	5	180
	6	64
	7	89
	8	75
	9	79
	10	547
	11	73
	12	100
	13	82
	14	78
	15	268
	16	145
	17	160
	18	451
	19	154
	20	656
	21	201
	22	259
	23	187
	24	305
	25	1881
	26	291
	27	306
	28	233
	29	220
	3700	2
	3756	1
	3900	1
	4000	2
	4050	2
		1
	4056	
	4356	1
	4463	1
	4471	1
	4500	1
	4563	1
	4720	1
	4770	1
	4900	1
		1
	4934	1
	5000	2
	5100	1
	5143	1
	5360	2
	5463	1
	5853	1
	5948	1
	6074	1
	6400	1
	7055	1
	7960	1
		1
	8000	
	8847	1
	9619	1
	9999	1
		RECORD, L
	manie.	TUCOKD, L

Name: RECORD, Length: 1336, dtype: int64

In [20]: sbrn.distplot(NYC_Property_data_2[NYC_Property_data_2['LTDEPTH']<=200]['LTDEPTH'],b
 ins=50)</pre>

Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x2108cd91940>

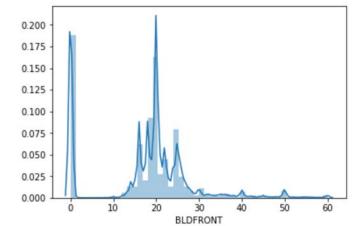


In [17]: NYC_Property_data_2.groupby('BLDFRONT').count()['RECORD']

Out[17]:	BLDFRONT		
Out[17].	0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29	224661 70 20 14 14 45 33 23 209 197 1385 143 2076 4854 15792 16013 73671 23821 76808 33073 193812 32593 53227 16036 32472 61770 28443 15112 9035 3841	
	900 911 961 982 1000 1102 1160 1169 1225 1227 1280 1362 1394 1812 1844 1925 1943 2025 2030 2500 3100 3285 4017 4149 5518 5614 6020 6414 7538 7575 Name:	1 1 1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	

Name: RECORD, Length: 610, dtype: int64

Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0x2108ce11ba8>

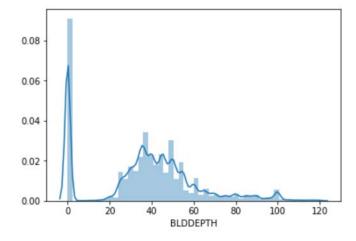


In [18]: NYC_Property_data_2.groupby('BLDDEPTH').count()['RECORD']

Out[18]:	BLDDE	PTH
	0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29	224699 52 9 90 60 51 48 13 53 14 535 22 174 54 133 673 416 213 1345 339 4305 896 3020 1459 9892 11491 14512 7243 19709 4605
	980 992 999 1000 1007 1075 1131 1150 1175 1222 1300 1375 1399 1971 1980 2023 2436 3104 3390 4500 4600 5000 5020 5641 6308 7360 8500 9388 9393 Name:	3 2 2 2 1 1 1 1 1 2 1 1 1 1 1 1 1 1 1 1

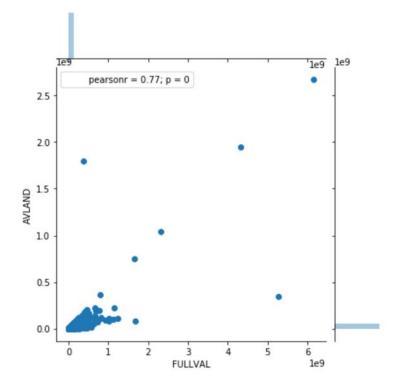
Name: RECORD, Length: 620, dtype: int64

Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x2108e21ee48>



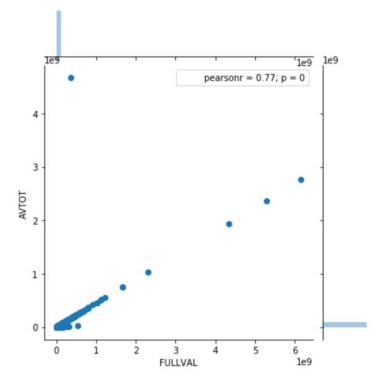
In [25]: sbrn.jointplot(x='FULLVAL',y='AVLAND',data=NYC_Property_data_3)

Out[25]: <seaborn.axisgrid.JointGrid at 0x2108e483b00>



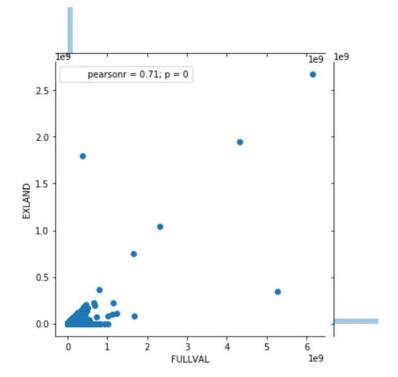
```
In [26]: sbrn.jointplot(x='FULLVAL',y='AVTOT',data=NYC_Property_data_3)
```

Out[26]: <seaborn.axisgrid.JointGrid at 0x2108e4961d0>



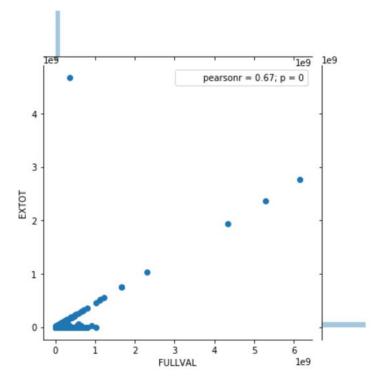
In [27]: sbrn.jointplot(x='FULLVAL',y='EXLAND',data=NYC_Property_data_3)

Out[27]: <seaborn.axisgrid.JointGrid at 0x2108e645898>



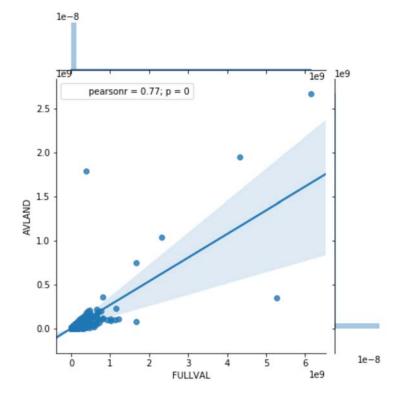
```
In [28]: sbrn.jointplot(x='FULLVAL',y='EXTOT',data=NYC_Property_data_3)
```

Out[28]: <seaborn.axisgrid.JointGrid at 0x2108e84f208>



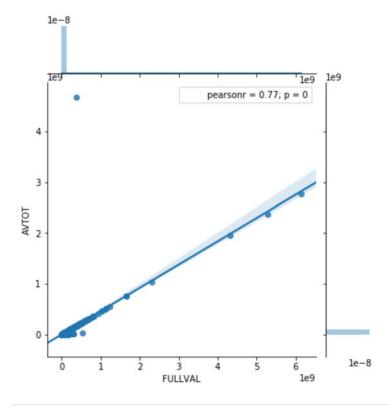
In [29]: sbrn.jointplot("FULLVAL", "AVLAND", data=NYC_Property_data_3, kind="reg")

Out[29]: <seaborn.axisgrid.JointGrid at 0x2108eb0fe48>



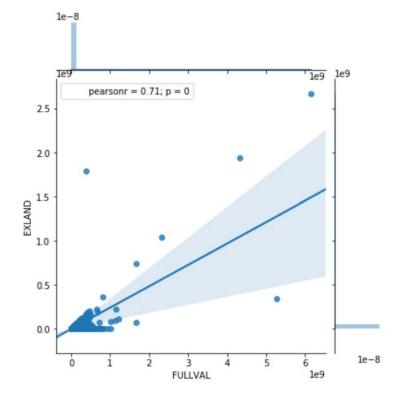
```
In [30]: sbrn.jointplot("FULLVAL", "AVTOT", data=NYC_Property_data_3, kind="reg")
```

Out[30]: <seaborn.axisgrid.JointGrid at 0x2108eb0f3c8>



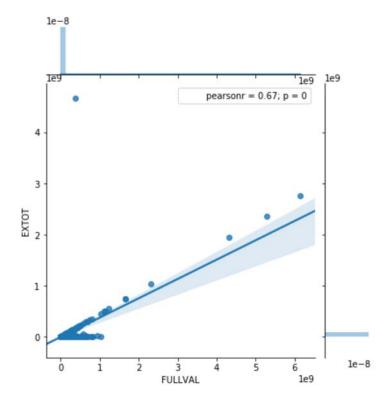
In [31]: sbrn.jointplot("FULLVAL", "EXLAND", data=NYC_Property_data_3, kind="reg")

Out[31]: <seaborn.axisgrid.JointGrid at 0x2108ff3d710>



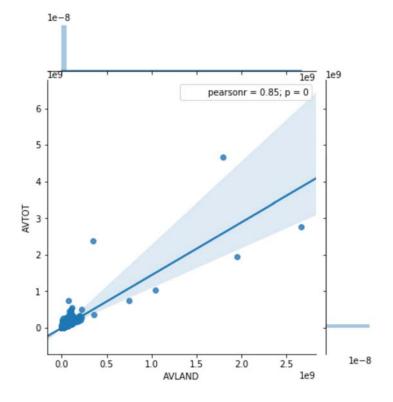
```
In [32]: sbrn.jointplot("FULLVAL", "EXTOT", data=NYC_Property_data_3, kind="reg")
```

Out[32]: <seaborn.axisgrid.JointGrid at 0x21090a532b0>



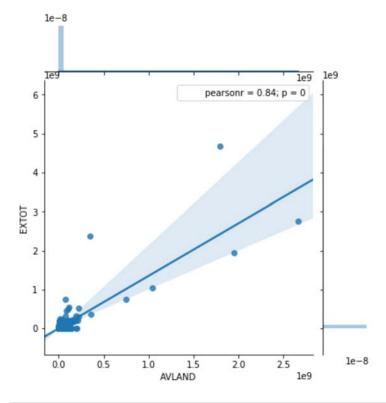
In [37]: sbrn.jointplot("AVLAND", "AVTOT", data=NYC_Property_data_3, kind="reg")

Out[37]: <seaborn.axisgrid.JointGrid at 0x210a02e2978>



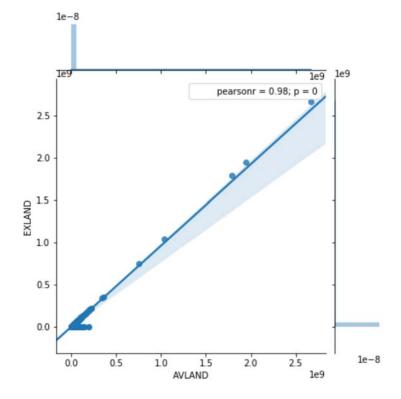
```
In [38]: sbrn.jointplot("AVLAND", "EXTOT", data=NYC_Property_data_3, kind="reg")
```

Out[38]: <seaborn.axisgrid.JointGrid at 0x210a2a08da0>



In [39]: sbrn.jointplot("AVLAND", "EXLAND", data=NYC_Property_data_3, kind="reg")

Out[39]: <seaborn.axisgrid.JointGrid at 0x210a2a33898>



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