Assignment is below.

In [1]:

```
from sklearn.svm import LinearSVC
from sklearn.linear_model import LogisticRegression
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
sns.set(font_scale=1.5)
import numpy as np

from pylab import rcParams
rcParams['figure.figsize'] = 20, 10


from sklearn.linear_model import LogisticRegression as Model
```

Read in the Kobe Bryant shooting data [https://www.kaggle.com/c/kobe-bryant-shot-selection]

In [2]:

```
kobe = pd.read_csv('../data/kobe.csv')
kobe.dropna(inplace=True)
```

In [3]:

```
list(kobe.columns)
```

Out[3]:

```
['action_type',
 'combined_shot_type',
 'game_event_id',
 'game_id',
 'lat',
 'loc_x',
 'loc_y',
 'lon',
 'minutes_remaining',
 'period',
 'playoffs',
 'season',
 'seconds_remaining',
 'shot_distance',
 'shot_made_flag',
 'shot_type',
 'shot_zone_area',
 'shot_zone_basic',
 'shot_zone_range',
 'team_id',
 'team_name',
 'game_date',
 'matchup',
 'opponent',
 'shot_id']
```

For now, use just the numerical datatypes. They are below as `num_columns`

In [4]:

```
kobe.shot_zone_area.value_counts()
```

Out[4]:

```
Center(C)                11289
```

```
Right Side Center(RC)     3981
Right Side(R)             3859
Left Side Center(LC)      3364
Left Side(L)              3132
Back Court(BC)              72
Name: shot_zone_area, dtype: int64
```

In [5]:

```
kobe.shot_zone_range.value_counts()
```

Out[5]:

```
Less Than 8 ft.    7857
16-24 ft.          6907
8-16 ft.           5580
24+ ft.            5281
Back Court Shot      72
Name: shot_zone_range, dtype: int64
```

In [6]:

```
kobe.shot_zone_basic.value_counts()
```

Out[6]:

```
Mid-Range                10532
Restricted Area           5932
Above the Break 3         4720
In The Paint (Non-RA)     3880
Right Corner 3             333
Left Corner 3              240
Backcourt                   60
Name: shot_zone_basic, dtype: int64
```

In [7]:

```
kobe
```

Out[7]:

	action_type	combined_shot_type	game_event_id	game_id	lat	loc_x	loc_y	lon	minutes_remaining	period	...	sh
1	Jump Shot	Jump Shot	12	20000012	34.0443	-157	0	-118.4268	10	1	...	2
2	Jump Shot	Jump Shot	35	20000012	33.9093	-101	135	-118.3708	7	1	...	2
3	Jump Shot	Jump Shot	43	20000012	33.8693	138	175	-118.1318	6	1	...	2
4	Driving Dunk Shot	Dunk	155	20000012	34.0443	0	0	-118.2698	6	2	...	2
5	Jump Shot	Jump Shot	244	20000012	34.0553	-145	-11	-118.4148	9	3	...	2
6	Layup Shot	Layup	251	20000012	34.0443	0	0	-118.2698	8	3	...	2
8	Jump Shot	Jump Shot	265	20000012	33.9363	-65	108	-118.3348	6	3	...	2
9	Running Jump Shot	Jump Shot	294	20000012	33.9193	-33	125	-118.3028	3	3	...	2
10	Jump Shot	Jump Shot	309	20000012	33.8063	-94	238	-118.3638	1	3	...	3
11	Jump Shot	Jump Shot	4	20000019	33.9173	121	127	-118.1488	11	1	...	2
12	Running Jump Shot	Jump Shot	27	20000019	33.9343	-67	110	-118.3368	7	1	...	2
13	Jump Shot	Jump Shot	66	20000019	34.0403	-94	4	-118.3638	2	1	...	2
14	Jump Shot	Jump Shot	80	20000019	33.9973	-23	47	-118.2928	1	1	...	2

	action_type	combined_shot_type	game_event_id	game_id	lat	loc_x	loc_y	lon	minutes_remaining	period	...	sh
15	Jump Shot	Jump Shot	86	20000019	33.8523	62	192	-118.2078	0	1	...	2
17	Jump Shot	Jump Shot	138	20000019	33.8183	-117	226	-118.3868	8	2	...	3
18	Jump Shot	Jump Shot	244	20000019	33.9473	-132	97	-118.4018	11	3	...	2
20	Jump Shot	Jump Shot	255	20000019	33.9003	3	144	-118.2668	10	3	...	2
21	Jump Shot	Jump Shot	265	20000019	33.9173	134	127	-118.1358	9	3	...	2
22	Running Jump Shot	Jump Shot	274	20000019	33.9343	-16	110	-118.2858	7	3	...	2
23	Running Jump Shot	Jump Shot	299	20000019	33.8943	-109	150	-118.3788	5	3	...	2
24	Running Jump Shot	Jump Shot	307	20000019	33.9813	-46	63	-118.3158	5	3	...	2
25	Layup Shot	Layup	332	20000019	34.0443	0	0	-118.2698	2	3	...	2
26	Jump Shot	Jump Shot	345	20000019	33.8483	-58	196	-118.3278	2	3	...	2
27	Jump Shot	Jump Shot	369	20000019	33.8583	-183	186	-118.4528	0	3	...	3
28	Jump Shot	Jump Shot	400	20000019	33.8713	85	173	-118.1848	8	4	...	2
29	Jump Shot	Jump Shot	429	20000019	33.9573	3	87	-118.2668	6	4	...	2
30	Running Jump Shot	Jump Shot	488	20000019	34.0403	121	4	-118.1488	1	4	...	2
31	Jump Shot	Jump Shot	499	20000019	34.0103	127	34	-118.1428	0	4	...	2
38	Jump Shot	Jump Shot	184	20000047	33.8603	91	184	-118.1788	3	2	...	2
39	Jump Shot	Jump Shot	202	20000047	33.7723	-27	272	-118.2968	0	2	...	3
...	...	...	...	...	...	...	...	...	...	...	...	
30661	Slam Dunk Shot	Dunk	245	49900087	34.0443	0	0	-118.2698	9	3	...	2
30662	Jump Shot	Jump Shot	259	49900087	33.9913	-8	53	-118.2778	8	3	...	2
30663	Jump Shot	Jump Shot	270	49900087	34.0193	106	25	-118.1638	6	3	...	2
30665	Layup Shot	Layup	280	49900087	34.0263	-14	18	-118.2838	5	3	...	2
30666	Jump Shot	Jump Shot	295	49900087	33.8733	-81	171	-118.3508	4	3	...	2
30667	Jump Shot	Jump Shot	368	49900087	33.7943	40	250	-118.2298	9	4	...	3
30669	Jump Shot	Jump Shot	425	49900087	33.9913	171	53	-118.0988	3	4	...	2
30670	Running Jump Shot	Jump Shot	15	49900088	34.0283	-74	16	-118.3438	9	1	...	2
30671	Driving Layup Shot	Layup	25	49900088	34.0443	0	0	-118.2698	8	1	...	2
30672	Jump Shot	Jump Shot	29	49900088	33.9893	89	55	-118.1808	8	1	...	2
30673	Jump Shot	Jump Shot	36	49900088	34.0443	117	0	-118.1528	7	1	...	2
30674	Jump Shot	Jump Shot	81	49900088	33.8283	117	216	-118.1528	2	1	...	3
30675	Jump Shot	Jump Shot	84	49900088	33.8283	-134	216	-118.4038	2	1	...	3
30676	Running Jump Shot	Jump Shot	98	49900088	34.0443	-141	0	-118.4108	0	1	...	2
30677	Jump Shot	Jump Shot	101	49900088	33.9013	-113	143	-118.3828	0	1	...	2

	action_type	combined_shot_type	game_event_id	game_id	lat	loc_x	loc_y	lon	minutes_remaining	period	...	sh
30678	Driving Layup Shot	Layup	181	49900088	34.0283	14	16	-118.2558	3	2	...	2
30679	Layup Shot	Layup	212	49900088	34.0443	0	0	-118.2698	0	2	...	2
30681	Jump Shot	Jump Shot	218	49900088	33.7833	-18	261	-118.2878	0	2	...	3
30683	Jump Shot	Jump Shot	228	49900088	33.8283	1	216	-118.2688	10	3	...	2
30684	Jump Shot	Jump Shot	231	49900088	33.9553	-96	89	-118.3658	10	3	...	2
30685	Jump Shot	Jump Shot	249	49900088	33.7943	81	250	-118.1888	7	3	...	3
30687	Jump Shot	Jump Shot	284	49900088	33.9443	40	100	-118.2298	3	3	...	2
30688	Jump Shot	Jump Shot	308	49900088	33.9833	-126	61	-118.3958	1	3	...	2
30689	Jump Shot	Jump Shot	326	49900088	33.3653	-12	679	-118.2818	0	3	...	3
30690	Jump Shot	Jump Shot	331	49900088	33.9443	-113	100	-118.3828	11	4	...	2
30691	Driving Layup Shot	Layup	382	49900088	34.0443	0	0	-118.2698	7	4	...	2
30692	Jump Shot	Jump Shot	397	49900088	33.9963	1	48	-118.2688	6	4	...	2
30694	Running Jump Shot	Jump Shot	426	49900088	33.8783	-134	166	-118.4038	3	4	...	2
30695	Jump Shot	Jump Shot	448	49900088	33.7773	31	267	-118.2388	2	4	...	3
30696	Jump Shot	Jump Shot	471	49900088	33.9723	1	72	-118.2688	0	4	...	2

25697 rows × 25 columns

In [8]:

```
kobe.shot_made_flag.value_counts(normalize=True)
```

Out[8]:

```
0.0    0.553839
1.0    0.446161
Name: shot_made_flag, dtype: float64
```

In [9]:

```
kobe.shot_made_flag.value_counts(normalize=False)
```

Out[9]:

```
0.0    14232
1.0    11465
Name: shot_made_flag, dtype: int64
```

In [10]:

```
num_columns = [col for col, dtype in zip(kobe.columns, kobe.dtypes) if dtype != 'object']
num_columns
```

Out[10]:

```
['game_event_id',
 'game_id',
 'lat',
 'loc_x',
 'loc_y',
 'lon',
 'minutes_remaining',
 'period',
```

```
 'playoffs',
 'seconds_remaining',
 'shot_distance',
 'shot_made_flag',
 'team_id',
 'shot_id']
```

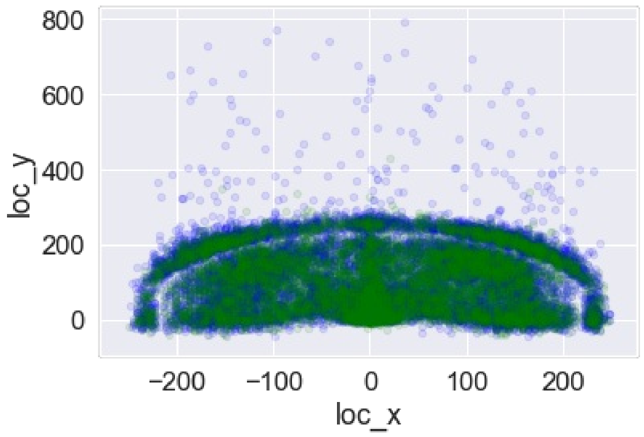
The `shot_made_flag` is the result (0 or 1) of the shot that Kobe took. Some of the values are missing (e.g. `NaN`) but we *dropped* them.

In [11]:

```
fig, ax = plt.subplots()
kobe[kobe.shot_made_flag==0].plot(kind='scatter', x='loc_x', y='loc_y', color='blue', alpha=0.1, ax
=ax)
kobe[kobe.shot_made_flag==1].plot(kind='scatter', x='loc_x', y='loc_y', color='green', alpha=0.1, a
x=ax)
# plt.scatter(kobe.loc_x, kobe.loc_y, alpha=0.2)
```

Out[11]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x238d32d0d30>
```

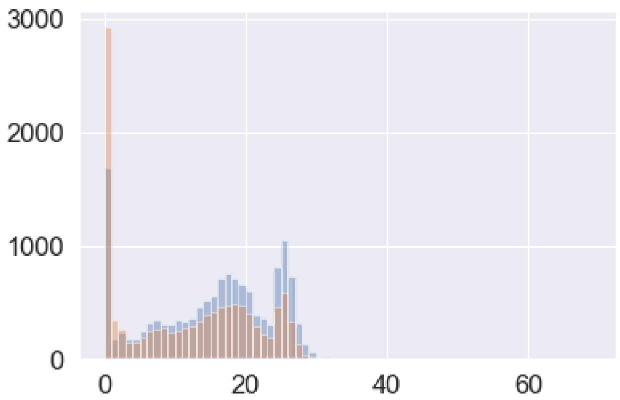


In [12]:

```
kobe[kobe.shot_made_flag==0].shot_distance.hist(bins=np.arange(0,70,1), alpha=.4)
kobe[kobe.shot_made_flag==1].shot_distance.hist(bins=np.arange(0,70,1), alpha=.4)
```

Out[12]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x238d3718630>
```

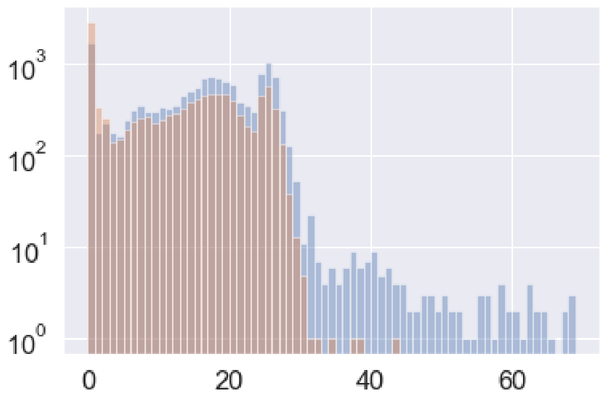


In [13]:

```
kobe[kobe.shot_made_flag==0].shot_distance.hist(bins=np.arange(0,70,1), alpha=.4, log=True)
kobe[kobe.shot_made_flag==1].shot_distance.hist(bins=np.arange(0,70,1), alpha=.4, log=True)
```

Out[13]:

<matplotlib.axes._subplots.AxesSubplot at 0x238d3c81550>



In [14]:

```
# fit a linear regression model and store the predictions
feature_cols = ['shot_distance', 'minutes_remaining']
X = kobe[feature_cols]
y = kobe.shot_made_flag

model = Model()
model.fit(X, y)
kobe['pred'] = model.predict(X)


from sklearn.metrics import accuracy_score
accuracy_score(kobe.shot_made_flag, kobe.pred.round())
```

Out[14]:

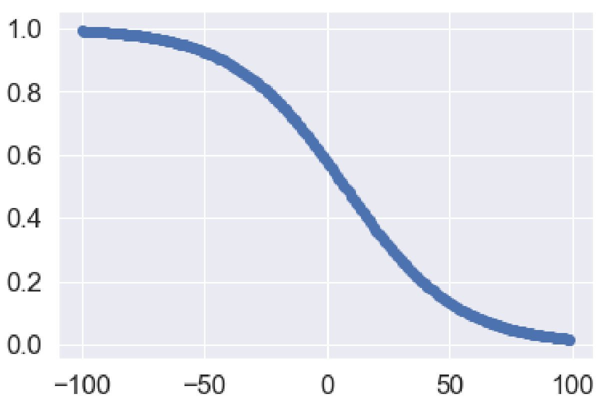
0.5971903335019653

In [15]:

```
distances = np.arange(-100, 100)
minutes = np.array([0]*200)
x_trial = np.column_stack((distances, minutes))
model.predict_proba(x_trial)
plt.scatter(distances, model.predict_proba(x_trial)[:,1])
```

Out[15]:

<matplotlib.collections.PathCollection at 0x238d3e7c470>

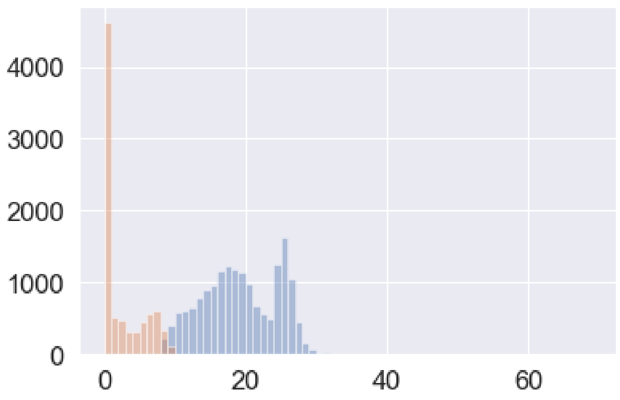


In [16]:

```
kobe[(kobe.pred==0)].shot_distance.hist(bins=np.arange(0,70,1), alpha=.4)
kobe[(kobe.pred==1)].shot_distance.hist(bins=np.arange(0,70,1), alpha=.4)
```

Out[16]:

<matplotlib.axes._subplots.AxesSubplot at 0x238d3f1f7f0>

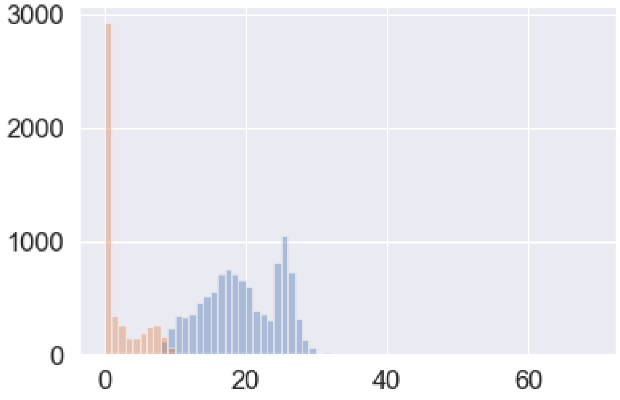


In [17]:

```
kobe[(kobe.pred==0) & (kobe.shot_made_flag==0)].shot_distance.hist(bins=np.arange(0,70,1), alpha=.4
)
kobe[(kobe.pred==1) & (kobe.shot_made_flag==1)].shot_distance.hist(bins=np.arange(0,70,1), alpha=.4
)
```

Out[17]:

<matplotlib.axes._subplots.AxesSubplot at 0x238d41a9470>

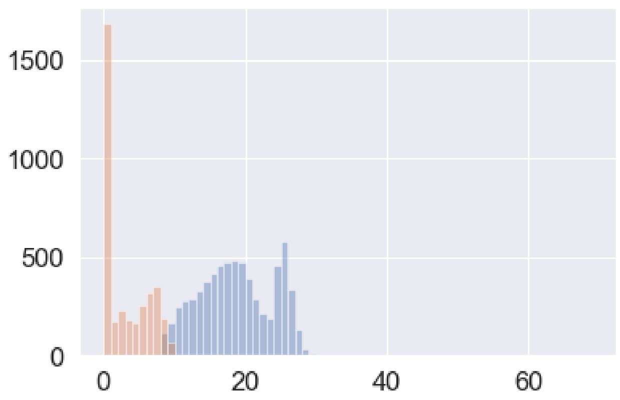


In [18]:

```
kobe[(kobe.pred==0) & (kobe.shot_made_flag==1)].shot_distance.hist(bins=np.arange(0,70,1), alpha=.4
)
kobe[(kobe.pred==1) & (kobe.shot_made_flag==0)].shot_distance.hist(bins=np.arange(0,70,1), alpha=.4
)
```

Out[18]:

<matplotlib.axes._subplots.AxesSubplot at 0x238d36d4080>

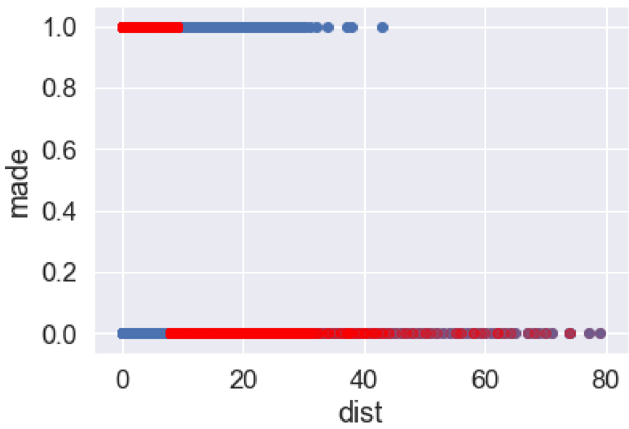


In [19]:

```
# scatter plot that includes the regression line
plt.scatter(kobe.shot_distance, kobe.shot_made_flag)
plt.scatter(kobe.shot_distance, kobe.pred, color='red', alpha=.2)
plt.xlabel('dist')
plt.ylabel('made')
```

Out[19]:

```
Text(0,0.5,'made')
```



The following is a reminder of how the SciKit-Learn Models can be interfaced

In [20]:

```
from sklearn.linear_model import LogisticRegression as Model
# from sklearn.tree import DecisionTreeClassifier as Model
# from sklearn.ensemble import RandomForestClassifier as Model
model = Model()

from sklearn.metrics import (accuracy_score,
                             classification_report,
                             confusion_matrix, auc, roc_curve
                            )
from sklearn.metrics import *
from sklearn import cross_validation

X_train, X_test, y_train, y_test = cross_validation.train_test_split(
    X, y, test_size=0.4, random_state=0)

cross_validation.cross_val_score(model, X, y, cv=10)
```

```
D:\Python\lib\site-packages\sklearn\cross_validation.py:41: DeprecationWarning: This module was de
precated in version 0.18 in favor of the model_selection module into which all the refactored
classes and functions are moved. Also note that the interface of the new CV iterators are differen
t from that of this module. This module will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

Out[20]:

```
array([0.59237651, 0.59354337, 0.59299611, 0.59688716, 0.61750973,
       0.58388478, 0.60334761, 0.60918645, 0.60140132, 0.58388478])
```

Assignment

Warmup. Perform some analysis on Kobe's shot selection. Ask and answer (with charts) questions such as: Does Kobe make more shots in the 4th quarter than on average? Does Kobe make more shots from the left more than the right? What was Kobe's best year for shooting percentage? Etc. The more naunced the more you'll have a feel for the data.

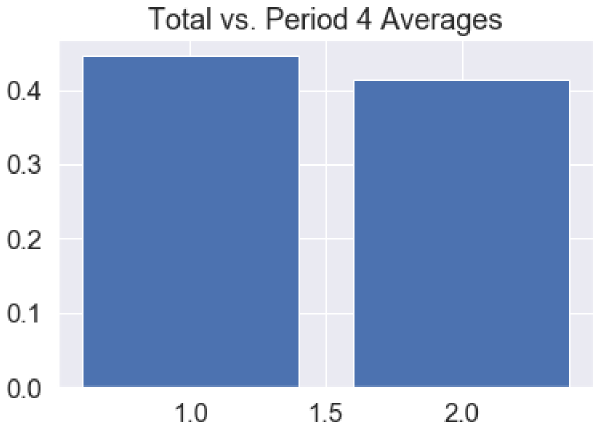
In [21]:

```
#Does Kobe make more shots in the 4th quarter than on average?

#All periods
average_all_periods = sum(kobe.shot_made_flag)/len(kobe.shot_made_flag)
print(average_all_periods)

#4th Quarter
kobe_period_4 = kobe[kobe.period == 4]
average_4th_period = sum(kobe_period_4.shot_made_flag)/len(kobe_period_4.shot_made_flag)
print(average_4th_period)

x=[1,2]
y=[0.44616103047048294,0.4137018037398643]


plt.bar(x,y)
plt.title('Total vs. Period 4 Averages')
```

```
0.44616103047048294
0.4137018037398643
```

Out[21]:

```
Text(0.5,1,'Total vs. Period 4 Averages')
```

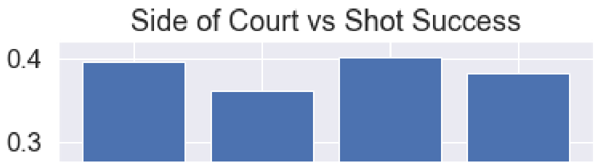


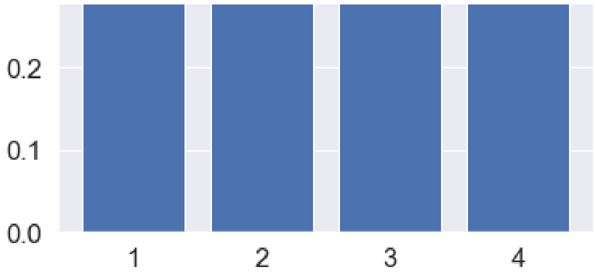
In [22]:

```
#Does Kobe make more shots from the left more than the right?

kobe_left = kobe[kobe.shot_zone_area == 'Left Side(L)']
kobe_left_2 = kobe[kobe.shot_zone_area == 'Left Side Center(LC)']

kobe_right = kobe[kobe.shot_zone_area == 'Right Side(R)']
kobe_right_2 = kobe[kobe.shot_zone_area == 'Right Side Center(RC)']

average_left= sum(kobe_left.shot_made_flag)/len(kobe_left.shot_made_flag)
average_left_2= sum(kobe_left_2.shot_made_flag)/len(kobe_left_2.shot_made_flag)
average_right= sum(kobe_right.shot_made_flag)/len(kobe_right.shot_made_flag)
average_right_2= sum(kobe_right_2.shot_made_flag)/len(kobe_right_2.shot_made_flag)

x2=[1,2,3,4]
y2=[average_left,average_left_2,average_right,average_right_2]

plt.bar(x2,y2)
plt.title('Side of Court vs Shot Success')
```

Out[22]:

```
Text(0.5,1,'Side of Court vs Shot Success')
```





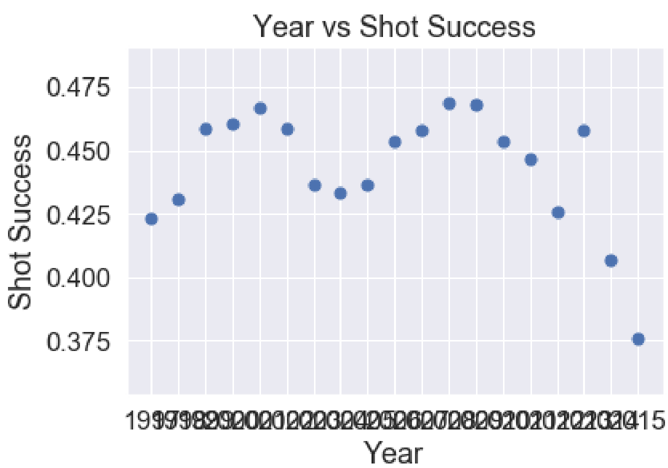
In [23]:

```
#What was Kobe's best year for shooting percentage?

kobe_1996_97= kobe[kobe.season == '1996-97']
kobe_1997_98= kobe[kobe.season == '1997-98']
kobe_1998_99= kobe[kobe.season == '1998-99']
kobe_1999_00= kobe[kobe.season == '1999-00']
kobe_2000_01= kobe[kobe.season == '2000-01']
kobe_2001_02= kobe[kobe.season == '2001-02']
kobe_2002_03= kobe[kobe.season == '2002-03']
kobe_2003_04= kobe[kobe.season == '2003-04']
kobe_2004_05= kobe[kobe.season == '2004-05']
kobe_2005_06= kobe[kobe.season == '2005-06']
kobe_2006_07= kobe[kobe.season == '2006-07']
kobe_2007_08= kobe[kobe.season == '2007-08']
kobe_2008_09= kobe[kobe.season == '2008-09']
kobe_2009_10= kobe[kobe.season == '2009-10']
kobe_2010_11= kobe[kobe.season == '2010-11']
kobe_2011_12= kobe[kobe.season == '2011-12']
kobe_2012_13= kobe[kobe.season == '2012-13']
kobe_2013_14= kobe[kobe.season == '2013-14']
kobe_2014_15= kobe[kobe.season == '2014-15']
kobe_2015_16= kobe[kobe.season == '2015-16']

average_1996_97= sum(kobe_1996_97.shot_made_flag)/len(kobe_1996_97.shot_made_flag)
average_1997_98= sum(kobe_1997_98.shot_made_flag)/len(kobe_1997_98.shot_made_flag)
average_1998_99= sum(kobe_1998_99.shot_made_flag)/len(kobe_1998_99.shot_made_flag)
average_1999_00= sum(kobe_1999_00.shot_made_flag)/len(kobe_1999_00.shot_made_flag)
average_2000_01= sum(kobe_2000_01.shot_made_flag)/len(kobe_2000_01.shot_made_flag)
average_2001_02= sum(kobe_2001_02.shot_made_flag)/len(kobe_2001_02.shot_made_flag)
average_2002_03= sum(kobe_2002_03.shot_made_flag)/len(kobe_2002_03.shot_made_flag)
average_2004_05= sum(kobe_2003_04.shot_made_flag)/len(kobe_2003_04.shot_made_flag)
average_2005_06= sum(kobe_2004_05.shot_made_flag)/len(kobe_2004_05.shot_made_flag)
average_2006_07= sum(kobe_2005_06.shot_made_flag)/len(kobe_2005_06.shot_made_flag)
average_2007_08= sum(kobe_2006_07.shot_made_flag)/len(kobe_2006_07.shot_made_flag)
average_2008_09= sum(kobe_2007_08.shot_made_flag)/len(kobe_2007_08.shot_made_flag)
average_2009_10= sum(kobe_2008_09.shot_made_flag)/len(kobe_2008_09.shot_made_flag)
average_2010_11= sum(kobe_2009_10.shot_made_flag)/len(kobe_2009_10.shot_made_flag)
average_2011_12= sum(kobe_2010_11.shot_made_flag)/len(kobe_2010_11.shot_made_flag)
average_2012_13= sum(kobe_2011_12.shot_made_flag)/len(kobe_2011_12.shot_made_flag)
average_2013_14= sum(kobe_2012_13.shot_made_flag)/len(kobe_2012_13.shot_made_flag)
average_2014_15= sum(kobe_2013_14.shot_made_flag)/len(kobe_2013_14.shot_made_flag)
average_2015_16= sum(kobe_2014_15.shot_made_flag)/len(kobe_2014_15.shot_made_flag)

x3=[1997,1998,1999,2000,2001,2002,2003,2004,2005,2006,2007,2008,2009,2010,2011,2012,2013,2014,2015
]
y3=[average_1996_97,
    average_1997_98,
    average_1998_99,
    average_1999_00,
    average_2000_01,
    average_2001_02,
    average_2002_03,
    average_2004_05,
    average_2005_06,
    average_2006_07,
    average_2007_08,
    average_2008_09,
    average_2009_10,
    average_2010_11,
    average_2011_12,
    average_2012_13,
    average_2013_14,
    average_2014_15,
    average_2015_16]
```

```
plt.scatter(x3,y3, s=50)
plt.title('Year vs Shot Success')
plt.xlabel('Year')
plt.xticks([1997,1998,1999,2000,2001,2002,2003,2004,2005,2006,2007,2008,2009,2010,2011,2012,2013,2
014,2015])
plt.ylabel('Shot Success')
```

Out[23]:

```
Text(0,0.5,'Shot Success')
```



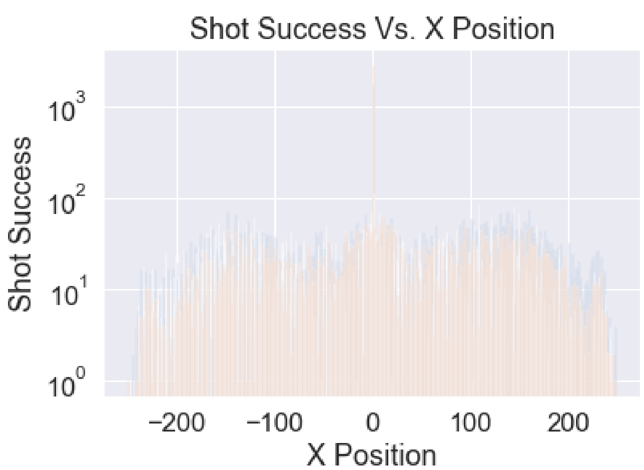
1. Create a new column called `abs_x` that is equal to the absolute value of loc_x. Plot a histogram of made shots and missed shots using this variable. Explain in detail (with graphics and evidence) why this could be a better feature/column to use in a Logsitic Regression model instead of `loc_x`.

In [24]:

```
#Histogram of loc_x
kobe[kobe.shot_made_flag==0].loc_x.hist(bins=np.arange(-250,250,1), alpha=.4, log=True)
kobe[kobe.shot_made_flag==1].loc_x.hist(bins=np.arange(-250,250,1), alpha=.4, log=True)
plt.title('Shot Success Vs. X Position')
plt.xlabel('X Position')
plt.ylabel('Shot Success')
```

Out[24]:

```
Text(0,0.5,'Shot Success')
```



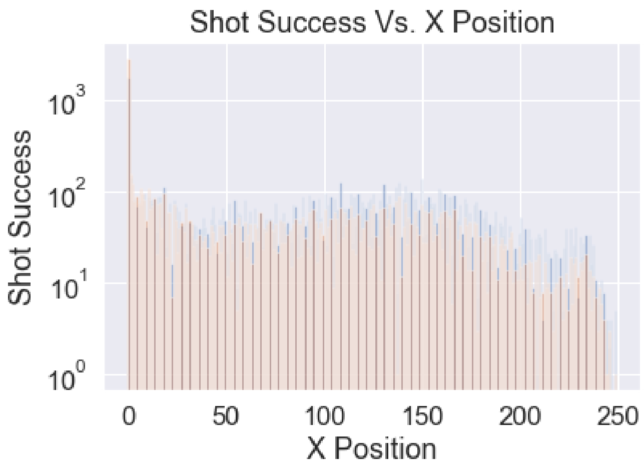
In [25]:

```
#Histogram of abs_x
kobe['abs_x'] = kobe['loc_x'].abs()
kobe[kobe.shot_made_flag==0].abs_x.hist(bins=np.arange(0,250,1), alpha=.4, log=True)
kobe[kobe.shot_made_flag==1].abs_x.hist(bins=np.arange(0,250,1), alpha=.4, log=True)
```

```
plt.title('Shot Success Vs. X Position')
plt.xlabel('X Position')
plt.ylabel('Shot Success')
```

Out[25]:

```
Text(0,0.5,'Shot Success')
```



In [26]:

```
#loc_x logistic regression model predictions
feature_cols = ['loc_y','loc_x']
X = kobe[feature_cols]
y = kobe.shot_made_flag

model = Model()
model.fit(X, y)
kobe['pred'] = model.predict(X)

from sklearn.metrics import accuracy_score
accuracy_score = accuracy_score(kobe.shot_made_flag, kobe.pred.round())
```

In [27]:

```
#abs_x logistic regression model predictions
feature_cols = ['loc_y','abs_x']
X = kobe[feature_cols]
y = kobe.shot_made_flag

model = Model()
model.fit(X, y)
kobe['pred'] = model.predict(X)

from sklearn.metrics import accuracy_score
abs_accuracy_score = accuracy_score(kobe.shot_made_flag, kobe.pred.round())
abs_accuracy_score
```

Out[27]:

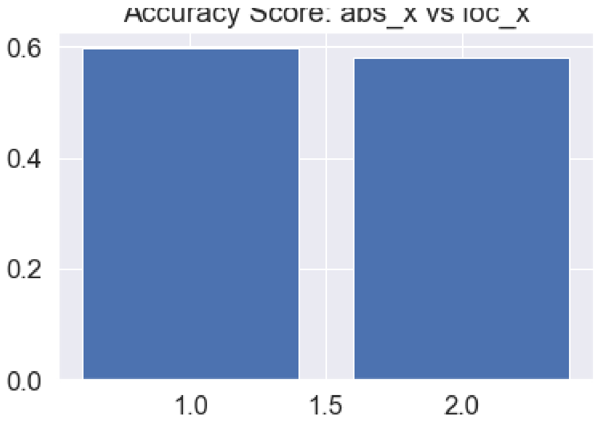
```
0.5977351441802545
```

In [28]:

```
#comparasion of model accuracy scores
x=[1,2]
y=[0.5977351441802545,0.5811962485893295]

plt.bar(x,y)
plt.title('Accuracy Score: abs_x vs loc_x')
```

Out[28]:

```
Text(0.5,1,'Accuracy Score: abs_x vs loc_x')
```



In [29]:

```
#Why is abs_x better than loc_x? abs_x contributes to a higher accuracy score, than loc_x
```

2. Convert several (including) string columns/features into numerical and attempt to use them in fitting a Logistic Regression model. Show histograms (similar to ones above) of made/missed of these new numerical features. Use these histograms to explain and justify why these features could improve the model

In [30]:

```
#I could not find a variable that would increase my accuracy_score() above what's calculated in line 14 (
0.5971903335019653). The two variables below 'combined_shot_type_numeric' and 'season_numeric' were the on
ly two I found that didn't significantly decrease the accuracy_score(). What did I miss?
```

In [31]:

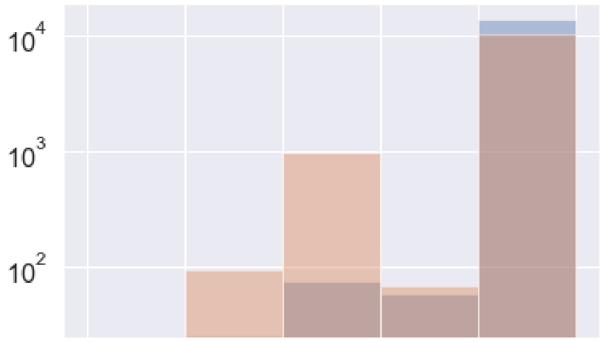
```
#convert 'combined_shot_type' to int64

kobe['combined_shot_type_numeric'] = np.nan

kobe.at[kobe.index[(kobe.combined_shot_type == 'Bank Shot')], 'combined_shot_type_numeric'] = '1'
kobe.at[kobe.index[(kobe.combined_shot_type == 'Dunk')], 'combined_shot_type_numeric'] = '2'
kobe.at[kobe.index[(kobe.combined_shot_type == 'Hook Shot')], 'combined_shot_type_numeric'] = '3'
kobe.at[kobe.index[(kobe.combined_shot_type == 'Jump Shot')], 'combined_shot_type_numeric'] = '4'
kobe.at[kobe.index[(kobe.combined_shot_type == 'Layup')], 'combined_shot_type_numeric'] = '5'
kobe.at[kobe.index[(kobe.combined_shot_type == 'Tip Shot')], 'combined_shot_type_numeric'] = '6'

kobe['combined_shot_type_numeric'] = pd.to_numeric(kobe['combined_shot_type_numeric'])
```

In [32]:

```
#combined_shot_type_numeric figure shot_made_flag
kobe[kobe.shot_made_flag==0].combined_shot_type_numeric.hist(bins=np.arange(0,6,1), alpha=.4, log=True)
kobe[kobe.shot_made_flag==1].combined_shot_type_numeric.hist(bins=np.arange(0,6,1), alpha=.4, log=True)
```

Out[32]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x238d38b6dd8>
```



In [33]:

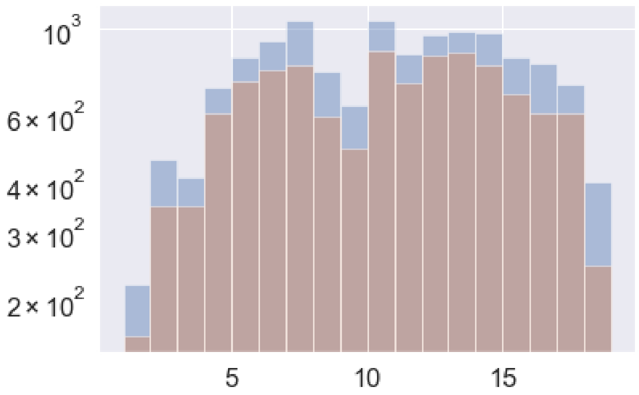
```
#convert season to int64
kobe.at[kobe.index[(kobe.season == '1996-97')], 'season_numeric'] = '1'
kobe.at[kobe.index[(kobe.season == '1997-98')], 'season_numeric'] = '2'
kobe.at[kobe.index[(kobe.season == '1998-99')], 'season_numeric'] = '3'
kobe.at[kobe.index[(kobe.season == '1999-00')], 'season_numeric'] = '4'
kobe.at[kobe.index[(kobe.season == '2000-01')], 'season_numeric'] = '5'
kobe.at[kobe.index[(kobe.season == '2001-02')], 'season_numeric'] = '6'
kobe.at[kobe.index[(kobe.season == '2002-03')], 'season_numeric'] = '7'
kobe.at[kobe.index[(kobe.season == '2003-04')], 'season_numeric'] = '8'
kobe.at[kobe.index[(kobe.season == '2004-05')], 'season_numeric'] = '9'
kobe.at[kobe.index[(kobe.season == '2005-06')], 'season_numeric'] = '10'
kobe.at[kobe.index[(kobe.season == '2006-07')], 'season_numeric'] = '11'
kobe.at[kobe.index[(kobe.season == '2007-08')], 'season_numeric'] = '12'
kobe.at[kobe.index[(kobe.season == '2008-09')], 'season_numeric'] = '13'
kobe.at[kobe.index[(kobe.season == '2009-10')], 'season_numeric'] = '14'
kobe.at[kobe.index[(kobe.season == '2010-11')], 'season_numeric'] = '15'
kobe.at[kobe.index[(kobe.season == '2011-12')], 'season_numeric'] = '16'
kobe.at[kobe.index[(kobe.season == '2012-13')], 'season_numeric'] = '17'
kobe.at[kobe.index[(kobe.season == '2013-14')], 'season_numeric'] = '18'
kobe.at[kobe.index[(kobe.season == '2014-15')], 'season_numeric'] = '19'
kobe.at[kobe.index[(kobe.season == '2015-16')], 'season_numeric'] = '20'

kobe['season_numeric'] = pd.to_numeric(kobe['season_numeric'])
```

In [34]:

```
#season_numeric figure
kobe[kobe.shot_made_flag==0].season_numeric.hist(bins=np.arange(1,20,1), alpha=.4, log=True)
kobe[kobe.shot_made_flag==1].season_numeric.hist(bins=np.arange(1,20,1), alpha=.4, log=True)
```

Out[34]:

<matplotlib.axes._subplots.AxesSubplot at 0x238d7326f28>



In [35]:

```
#game_date to useable format
kobe['game_date'] = pd.to_datetime(kobe['game_date'])
```

In [36]:

```
# fit a logistic regression model and store the predictions
feature_cols = ['combined_shot_type_numeric','season_numeric', 'shot_distance', 'minutes_remaining']
X = kobe[feature_cols]
y = kobe.shot_made_flag

model = Model()
model.fit(X, y)
kobe['pred'] = model.predict(X)


from sklearn.metrics import accuracy_score
accuracy_score(kobe.shot_made_flag, kobe.pred.round())
```

Out[36]:

```
0.5952834961279527
```

In [37]:

```
kobe.dtypes
```

Out[37]:

```
action_type                                object
combined_shot_type                         object
game_event_id                               int64
game_id                                     int64
lat                                       float64
loc_x                                       int64
loc_y                                       int64
lon                                       float64
minutes_remaining                           int64
period                                      int64
playoffs                                    int64
season                                     object
seconds_remaining                           int64
shot_distance                               int64
shot_made_flag                            float64
shot_type                                  object
shot_zone_area                             object
shot_zone_basic                            object
shot_zone_range                            object
team_id                                     int64
team_name                                  object
game_date                          datetime64[ns]
matchup                                    object
opponent                                   object
shot_id                                     int64
pred                                      float64
abs_x                                       int64
combined_shot_type_numeric                  int64
season_numeric                              int64
dtype: object
```

3. Show a 3 dimensional surface plot [https://matplotlib.org/mpl_toolkits/mplot3d/tutorial.html#surface-plots] of probabilities from a trained Logistic Regression model using only `abs_x` and `loc_y`. The probabilities arise from a distributed grid of `x` values and `y` values as input to the `predict_proba()` function.

In [38]:

```
# logistic regression model abs_x and loc_y
feature_cols = ['abs_x','loc_y']
X = kobe[feature_cols]
y = kobe.shot_made_flag

model = Model()
model.fit(X, y)
kobe['pred'] = model.predict(X)


from sklearn.metrics import accuracy_score
accuracy_score(kobe.shot_made_flag, kobe.pred.round())

distances = np.arange(0, 250)
y_locations = np.arange(0, 250)
x_trial = np.column_stack((distances, y_locations))
three_dee = model.predict_proba(x_trial)
```

In [40]:

```
x = kobe.abs_x
```

In [41]:

```
y = kobe.loc_y
```

In [42]:

```python
z = kobe['pred']
```

In [43]:

```python
from mpl_toolkits.mplot3d import Axes3D
fig = plt.figure()
ax = fig.add_subplot(111,projection='3d')

ax.scatter(x,y,z)
plt.show()
```