In [1]:
```
1 import pandas as pd
2
3 data = pd.read_csv('RawData.csv')
4 data.tail()
```

Out[1]:

	Date	Name	Team	Season	Round	Home Team	Away Team	Home Score	Away Score	Mar
146602	2003-03-30 00:00:00	Wayne Carey	Adelaide	2003.0	1	Adelaide	Fremantle	145	89	
146603	2003-03-30 00:00:00	Brett Burton	Adelaide	2003.0	1	Adelaide	Fremantle	145	89	
146604	2003-03-30 00:00:00	Matthew Bode	Adelaide	2003.0	1	Adelaide	Fremantle	145	89	
146605	2003-03-30 00:00:00	Rhett Biglands	Adelaide	2003.0	1	Adelaide	Fremantle	145	89	
146606	2003-03-30 00:00:00	Mark Bickley	Adelaide	2003.0	1	Adelaide	Fremantle	145	89	

5 rows × 32 columns

1 Cleaning

In [2]:
```
1 games = data.drop_duplicates(subset=['Date', 'Home Team', 'Away Te
2    'Date', 'Season', 'Round', 'Home Team', 'Away Team',
3        'Home Score', 'Away Score', 'Margin',
4 ]]
5 games
```

Out[2]:

	Date	Season	Round	Home Team	Away Team	Home Score	Away Score	Margin
0	2019-09-28 00:00:00	2019.0	GF	Richmond	Greater Western Sydney	114	25	89
44	2019-09-21 00:00:00	2019.0	PF	Collingwood	Greater Western Sydney	52	56	-4
88	2019-09-20 00:00:00	2019.0	PF	Geelong	Richmond	66	85	-19
132	2019-09-14 00:00:00	2019.0	SF	Brisbane Lions	Greater Western Sydney	80	83	-3
176	2019-09-13 00:00:00	2019.0	SF	Geelong	West Coast	88	68	20
...	...	...	...	...	...	...	...	...

	Date	Season	Round	Home Team	Away Team	Home Score	Away Score	Margin
146388	2003-04-26 00:00:00	2003.0	5	Adelaide	Port Adelaide	66	78	-12
146432	2003-04-20 00:00:00	2003.0	4	Adelaide	West Coast	106	73	33
146476	2003-04-13 00:00:00	2003.0	3	Sydney	Adelaide	76	103	-27
146520	2003-04-05 00:00:00	2003.0	2	St Kilda	Adelaide	99	91	8

We have 3333 games in total (what a cool number). 3151 games have Brownlow votes and 182 of them (5.4%) do not. For simplicity I will removed these games

In [3]:
```
# Number of games with votes
data[data['Brownlow Votes'] == 3].shape[0]
```

Out[3]: 3151

In [4]:
```
import numpy as np

def preprocess(data=data):
    """
    Extract Year information
    Set GameID=Day+HomeTeam for each game
    Set Win_True and Win_False columns to tell if the player won t
    Remove if game doesn't have votes
    """
    data['Year'] = data['Date'].str.extract(r"(\d{4})-*")
    data['Year'] = pd.to_numeric(data['Year'])

    data['Day'] = data['Date'].str.extract(r"(\d{4}-\d{2}-\d{2})")

    data['GameID'] = data['Day'] + data['Home Team']

    data['Win'] = ((data['Team'] == data['Away Team']) & (data['Ma
        | ((data['Team'] == data['Home Team']) & (data['Margin'] >
    data = pd.get_dummies(data, columns=['Win'])

    # games with other than 6 votes (1+2+3) are removed
    games = data.groupby('GameID')['Brownlow Votes'].agg('sum')
    valid_gameIDs = games[np.where(games==6)[0]].index
    data = data[data['GameID'].isin(valid_gameIDs)]

    del(data['Day'])
    del(data['Date'])
    return data
```

In [5]:
```
clean = preprocess(data)
```

It shows that for each game, there are 22 players on each side. There is one special case where there are only 21 players in a team, which was Adelaide on 2003-03-30. Could just be

a cut-off during scrapping?

In [6]:
```
for i, g in clean.groupby(['Team', 'GameID']):
    if g.shape[0] != 22:
        print(g.shape[0])
        print(g[['Team', 'GameID']].iloc[0])
```

```
21
Team                Adelaide
GameID    2003-03-30Adelaide
Name: 146586, dtype: object
```

In [7]:
```
# Splify by removing this game:
clean = clean[clean['GameID'] != '2003-03-30Adelaide']
```

In [8]:
```
train = clean[clean['Year'] <= 2015]
test = clean[clean['Year'] > 2015]
del(clean)
del(data)
```

In [9]:
```
print(train.shape)
print(test.shape)
```

```
(104940, 35)
(33660, 35)
```

2 Exploration

The number of games in `train` is 2333:

In [10]:
```
games = train.drop_duplicates(subset=['Home Team', 'Away Team', 'M
   'Season', 'Round', 'Home Team', 'Away Team',
       'Home Score', 'Away Score', 'Margin',
]]
games
```

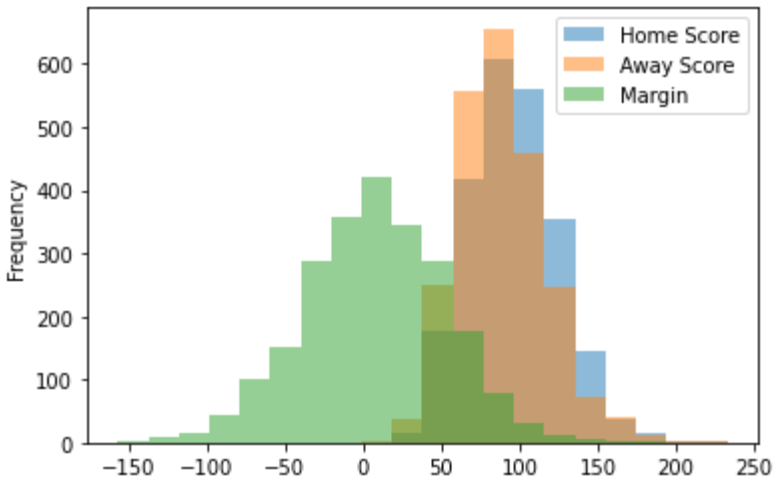
Out[10]:

	Season	Round	Home Team	Away Team	Home Score	Away Score	Margin
27412	2015.0	16	Gold Coast	Greater Western Sydney	79	94	-15
27456	2015.0	4	Greater Western Sydney	Gold Coast	119	53	66
27500	2014.0	6	Gold Coast	Greater Western Sydney	134	94	40
27544	2013.0	23	Gold Coast	Greater Western Sydney	146	63	83
27588	2013.0	5	Greater Western Sydney	Gold Coast	104	148	-44
...	...	...	...	...	...	...	...
146344	2003.0	6	North Melbourne	Adelaide	70	124	-54

	Season	Round	Home Team	Away Team	Home Score	Away Score	Margin
146388	2003.0	5	Adelaide	Port Adelaide	66	78	-12
146432	2003.0	4	Adelaide	West Coast	106	73	33
146476	2003.0	3	Sydney	Adelaide	76	103	-27
146520	2003.0	2	St Kilda	Adelaide	99	91	8

In [11]:
```
games[['Home Score', 'Away Score', 'Margin']].plot.hist(bins=20, a
```

Out[11]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f96da63a410>
```



It shows that the Margin's mean is positive, meaning on average Home Score is higher than Away Score. Does this mean Home wins more than Away?

In [12]:
```
games['Home_won'] = games['Margin'] > 0
games['Home_won'].value_counts()
```

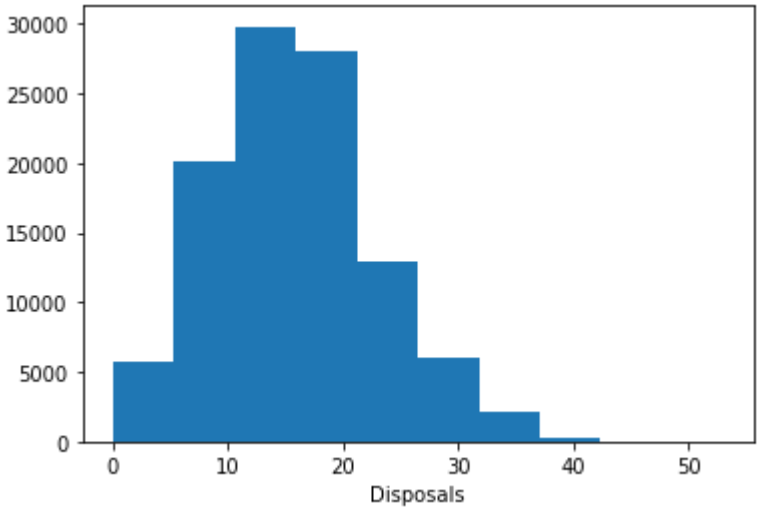
Out[12]:
```
True     1323
False    1010
Name: Home_won, dtype: int64
```

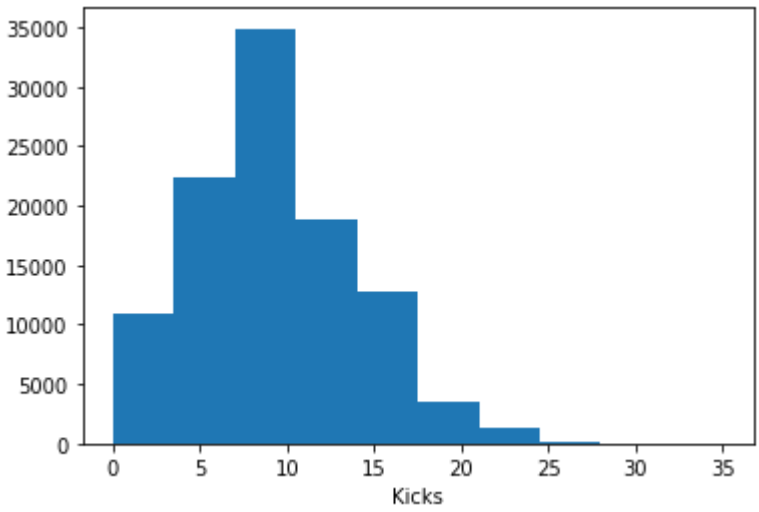
The number of Home wins is 1.3 times the number of Away wins.

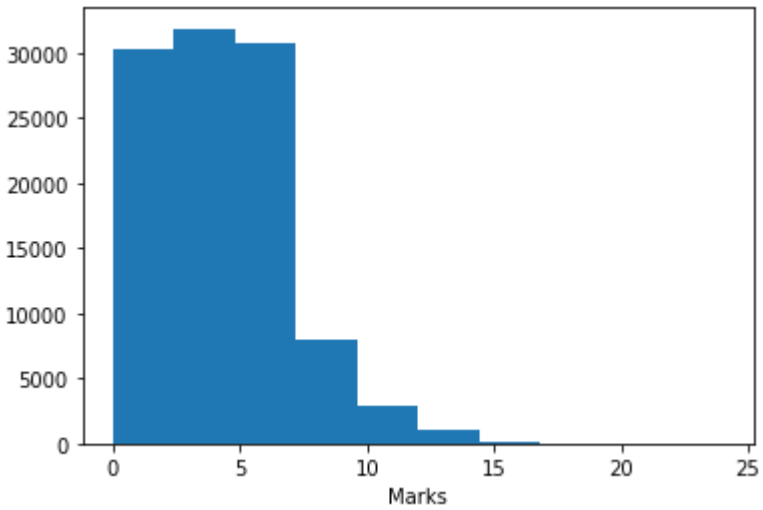
Next, let's show the distribution of performance indices:

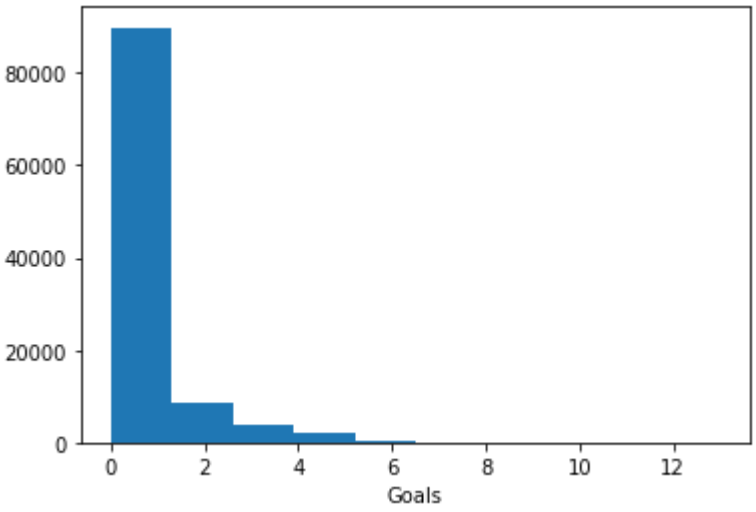
In [13]:
```
import matplotlib.pyplot as plt


perf_idx = ['Disposals', 'Kicks', 'Marks',
       'Handballs', 'Goals', 'Behinds', 'Hitouts', 'Tackles', 'Reb
       'Inside 50s', 'Clearances', 'Clangers', 'Frees For', 'Frees
       'Contested Pos', 'Uncontested Pos', 'Contested Marks',
       'Marks Inside 50', 'One Percenters', 'Goal Assists', 'Brown
       'TOG', 'Win_False', 'Win_True']

def histogram(data, col):
```

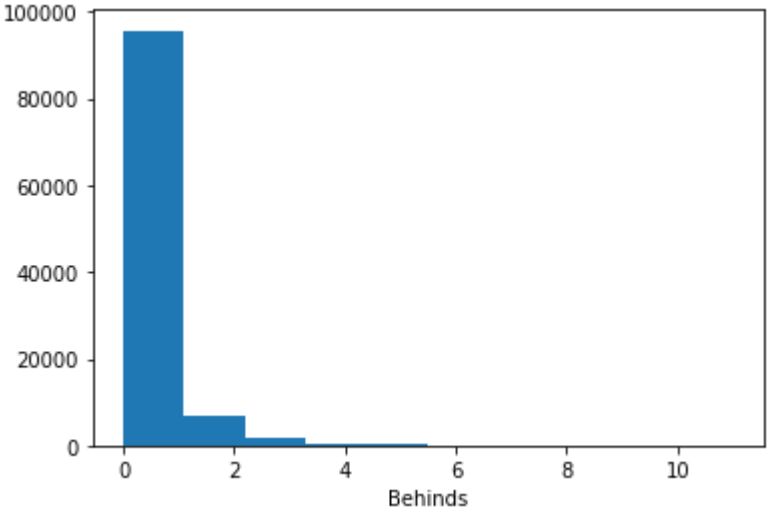
```
    fig, ax = plt.subplots()
    ax.hist(data[col])
    ax.set_xlabel(col)
    plt.show()

for p in perf_idx:
    histogram(train, p)
```

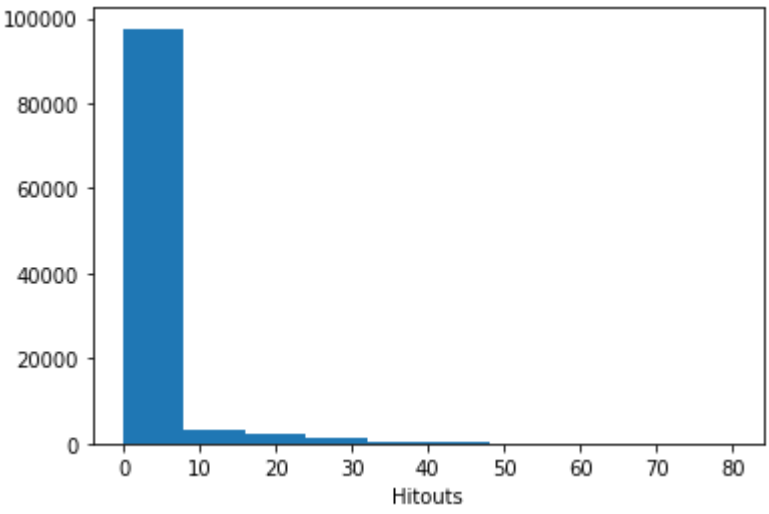







80000
60000
40000
20000
0
0
2
4
6
8
10
12
Goals


100000
80000
60000
40000
20000
0
0
2
4
6
8
10
Behinds


100000
80000
60000
40000
20000
0
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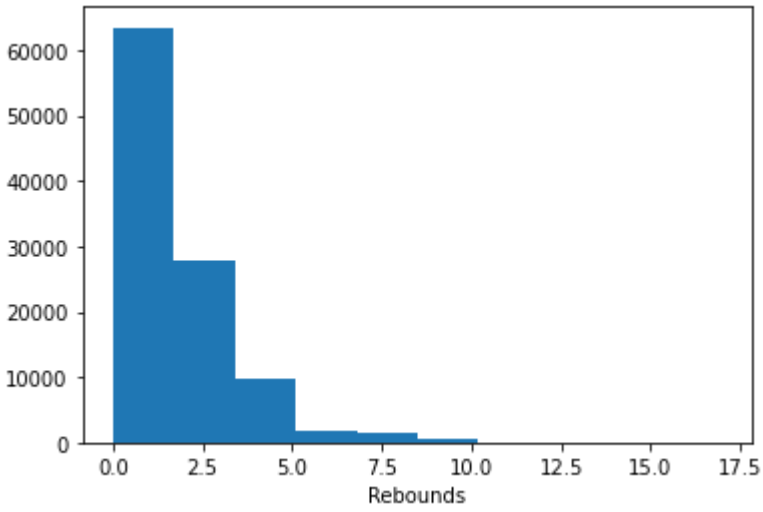
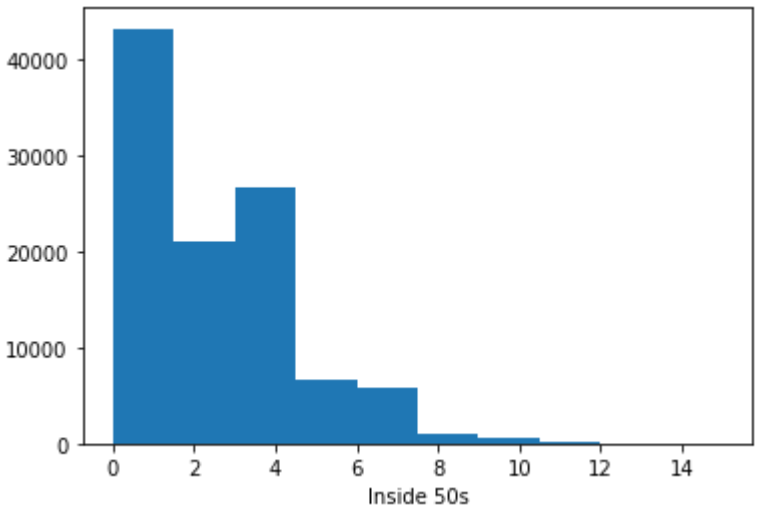
10
20
30
40
50
60
70
80
Hitouts


40000
35000
30000
25000
20000


60000
50000
40000
30000
20000
10000
0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
Rebounds


40000
30000
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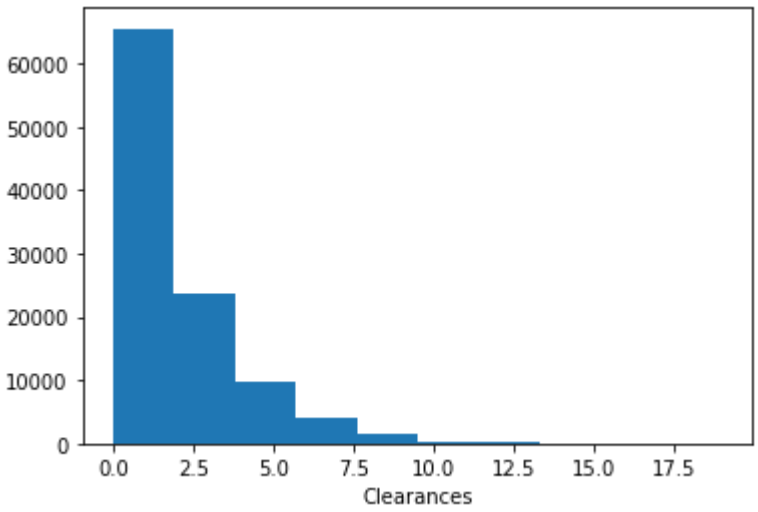
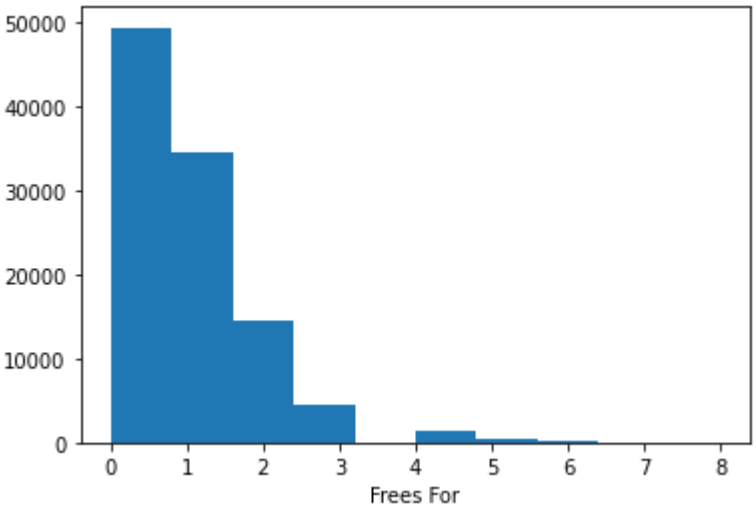
10000
0
0
2
4
6
8
10
12
14
Inside 50s


60000
50000
40000
30000
20000
10000
0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
Clearances


40000
30000


50000
40000
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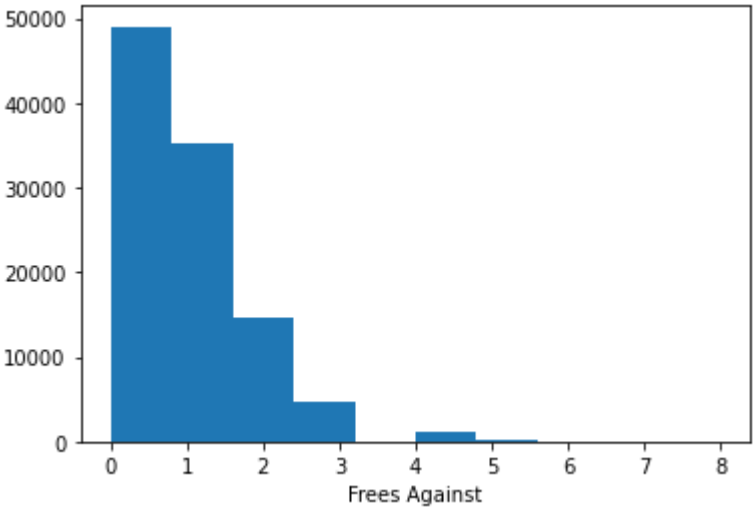
20000
10000
0
0 1 2 3 4 5 6 7 8
Frees For


50000
40000
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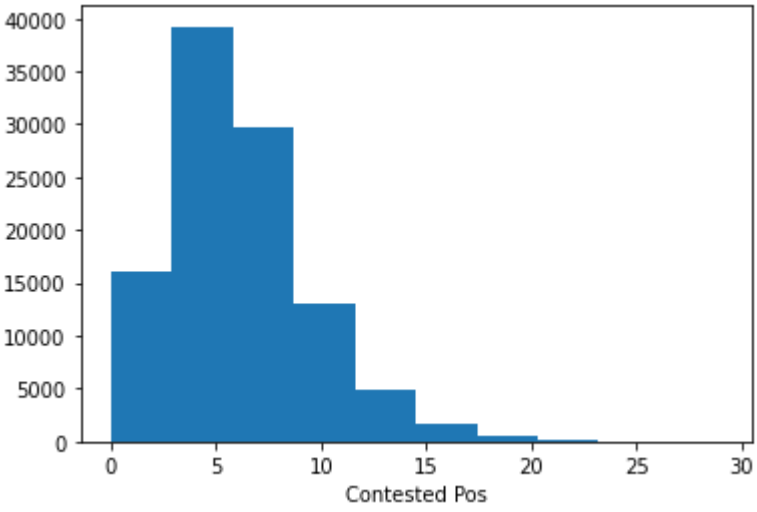
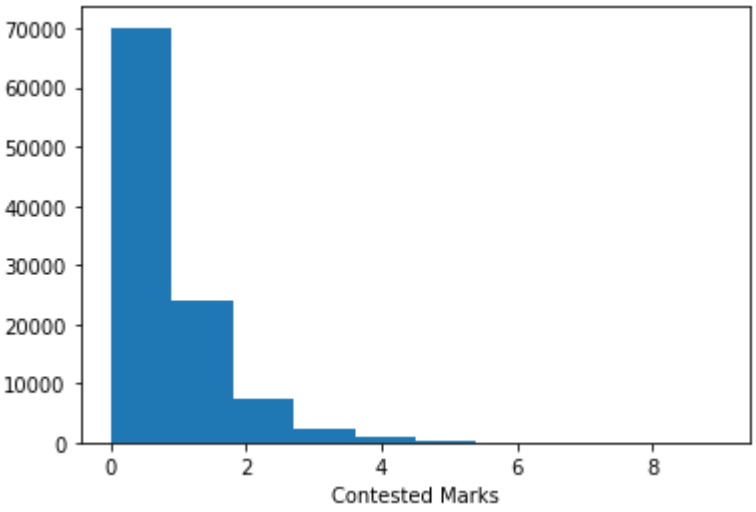
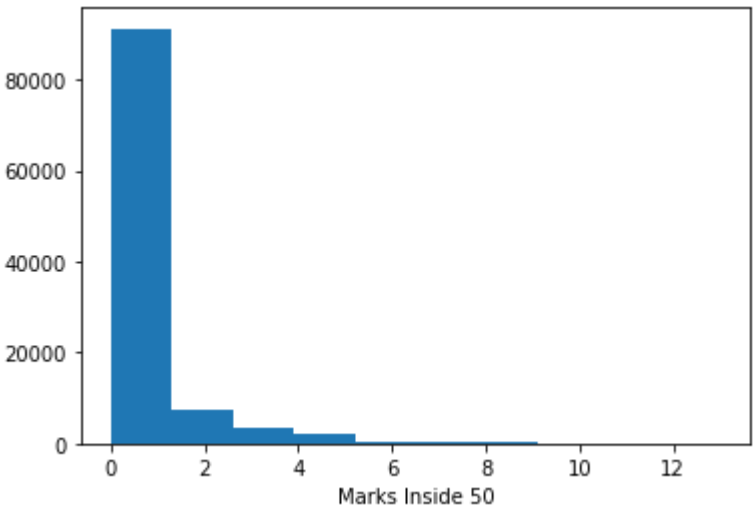
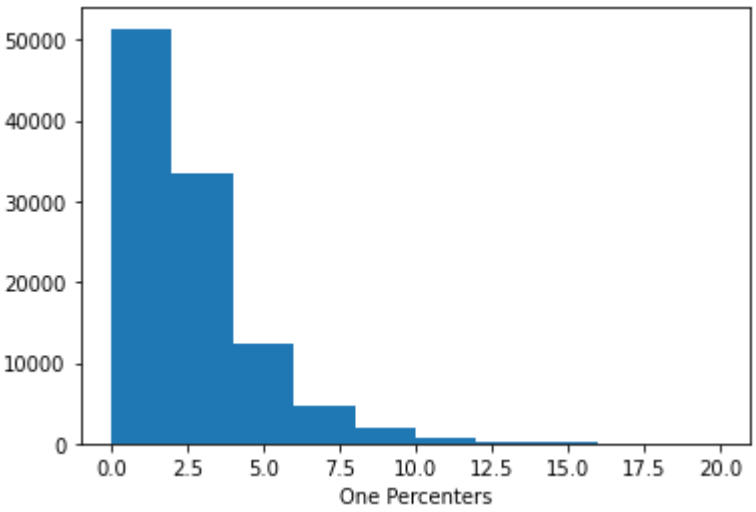
20000
10000
0
0 1 2 3 4 5 6 7 8
Frees Against


40000
35000
30000
25000
20000
15000
10000
5000
0
0 5 10 15 20 25 30
Contested Pos

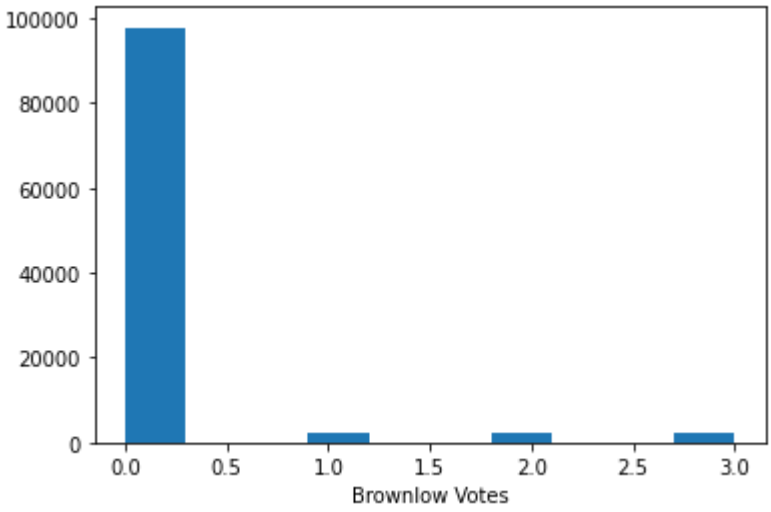

30000
25000
20000
15000

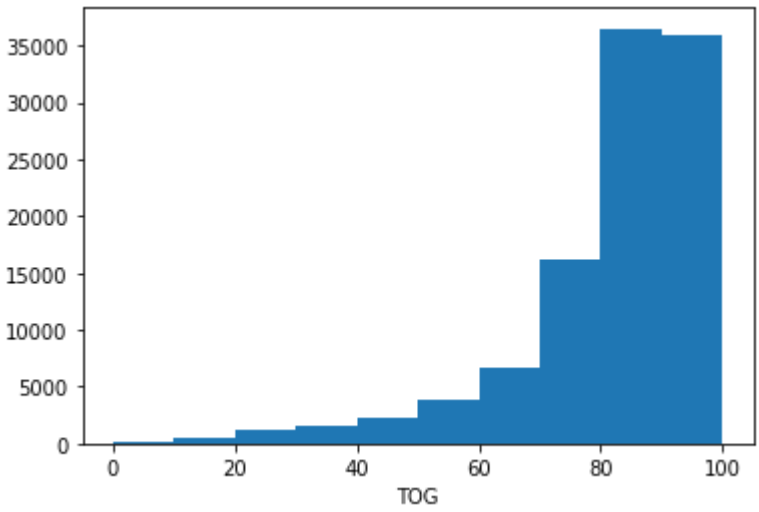

70000
60000
50000
40000
30000
20000
10000
0
0
2
4
6
8
Contested Marks

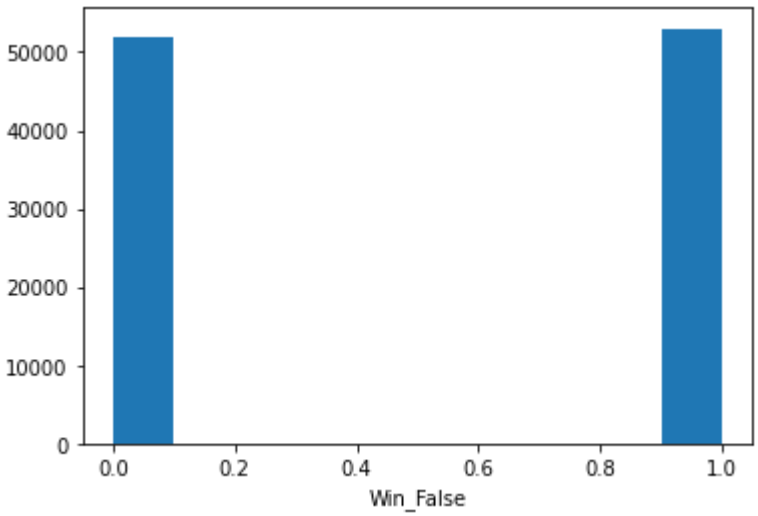

80000
60000
40000
20000
0
0
2
4
6
8
10
12
Marks Inside 50


50000
40000
30000
20000
10000
0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
One Percenters


70000
60000
50000
40000


100000
80000
60000
40000
20000
0
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Brownlow Votes


35000
30000
25000
20000
15000
10000
5000
0
0
20
40
60
80
100
TOG


50000
40000
30000
20000
10000
0
0.0
0.2
0.4
0.6
0.8
1.0
Win_False

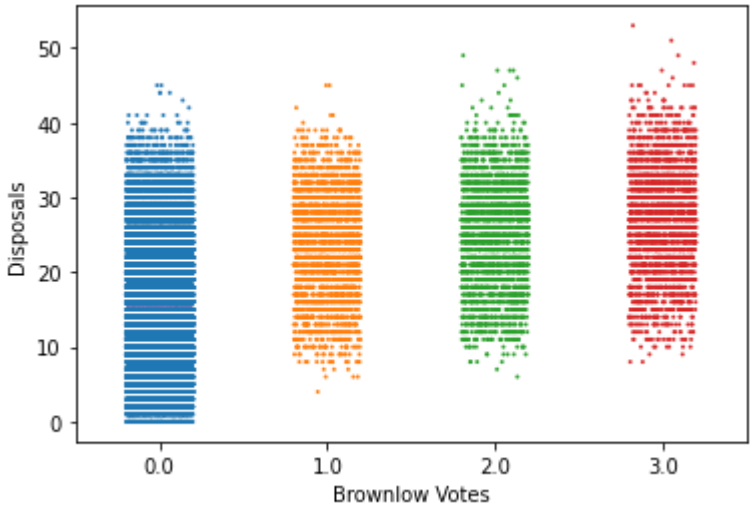

50000
40000
30000

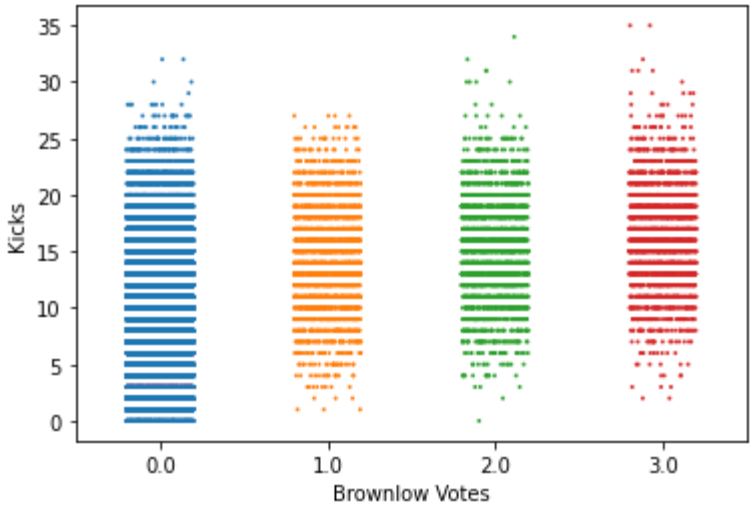
We specifically care about the difference between the normal players and the voted ones:

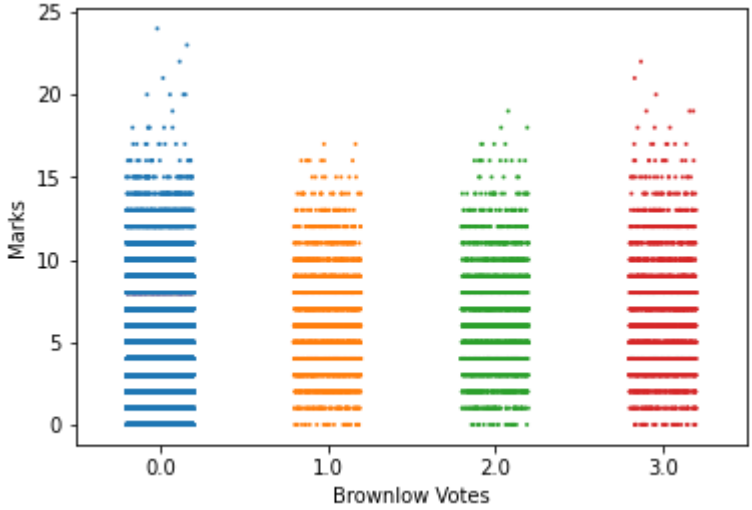
In [14]:

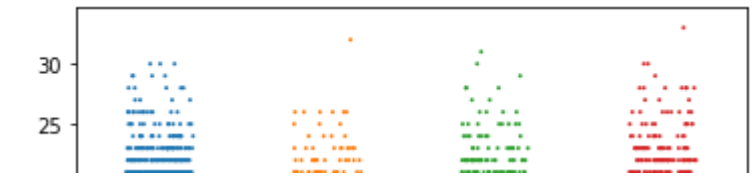
```
import seaborn as sns
def scatter_by_votes(data, col):
    fig, ax = plt.subplots()
    sns.stripplot(train['Brownlow Votes'], train[col], jitter=0.2,
    plt.show()
```

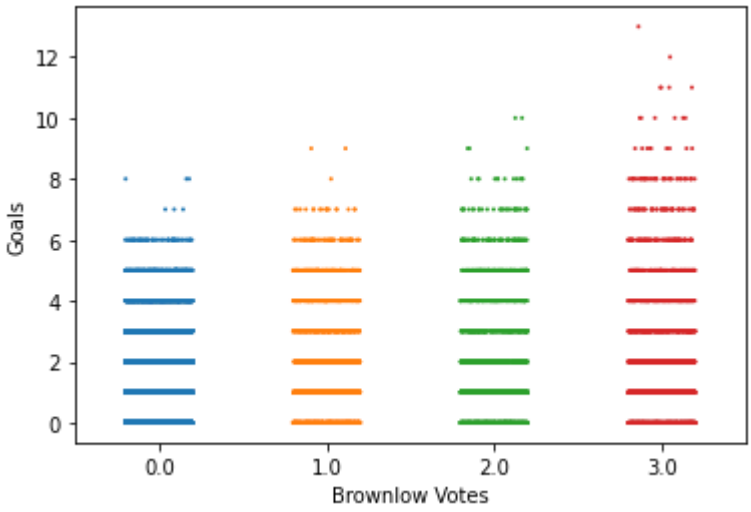
In [15]:
```
for p in perf_idx:
    scatter_by_votes(train, p)
```

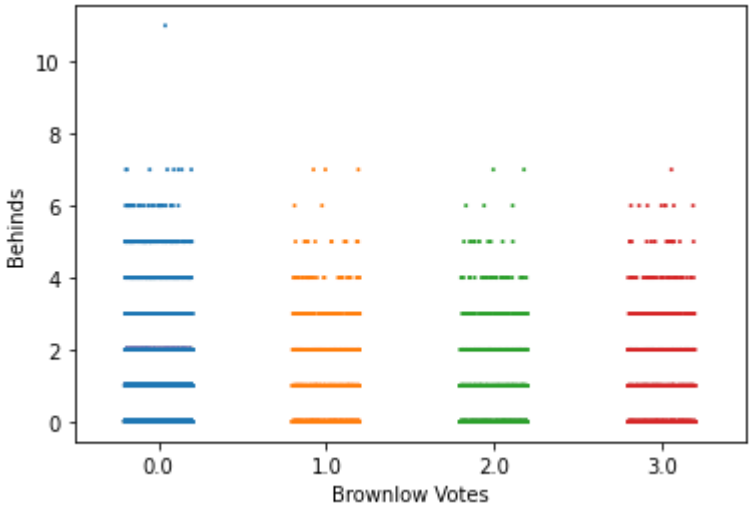


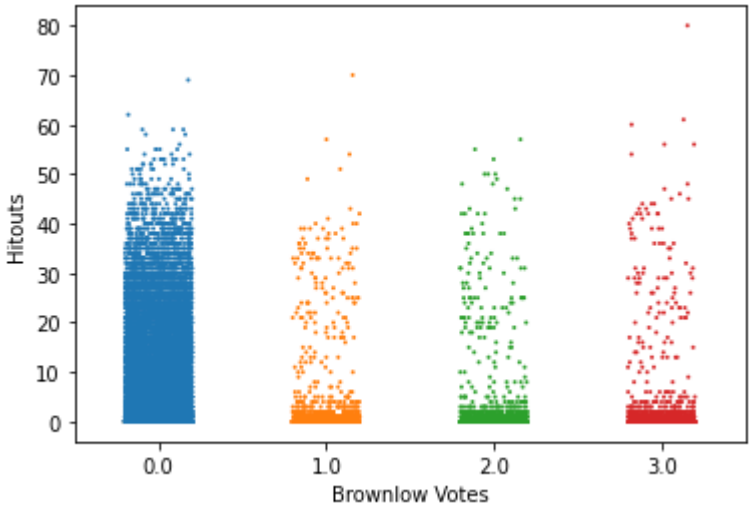


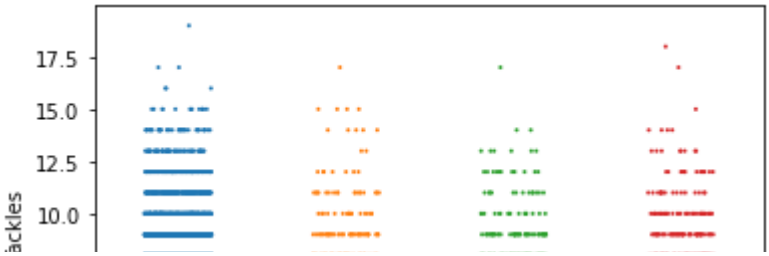


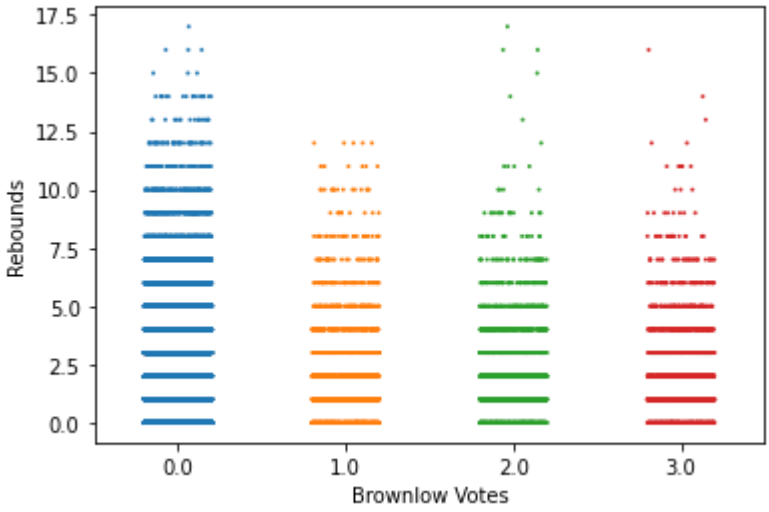


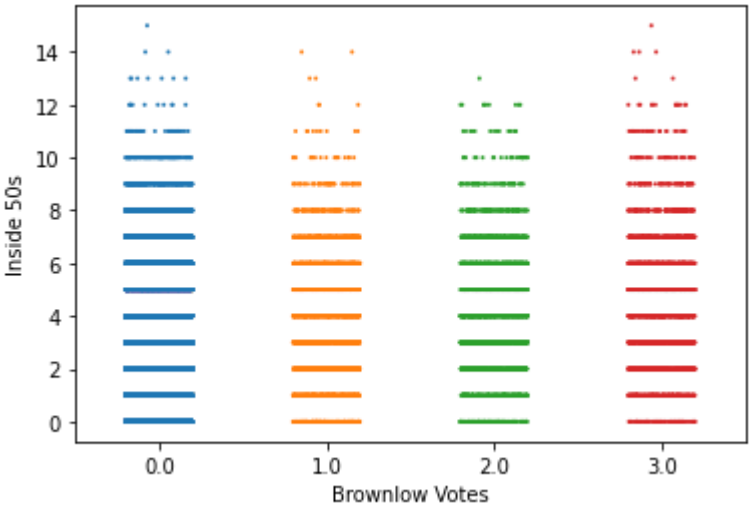

Goals
0
2
4
6
8
10
12
0.0
1.0
2.0
3.0
Brownlow Votes

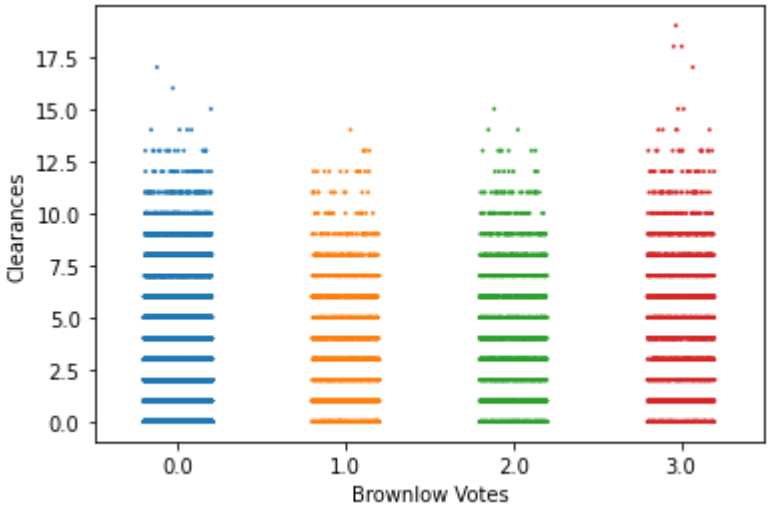

Behinds
0
2
4
6
8
10
0.0
1.0
2.0
3.0
Brownlow Votes

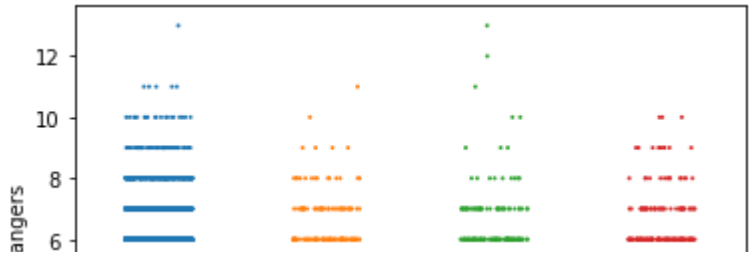

Hitouts
0
10
20
30
40
50
60
70
80
0.0
1.0
2.0
3.0
Brownlow Votes

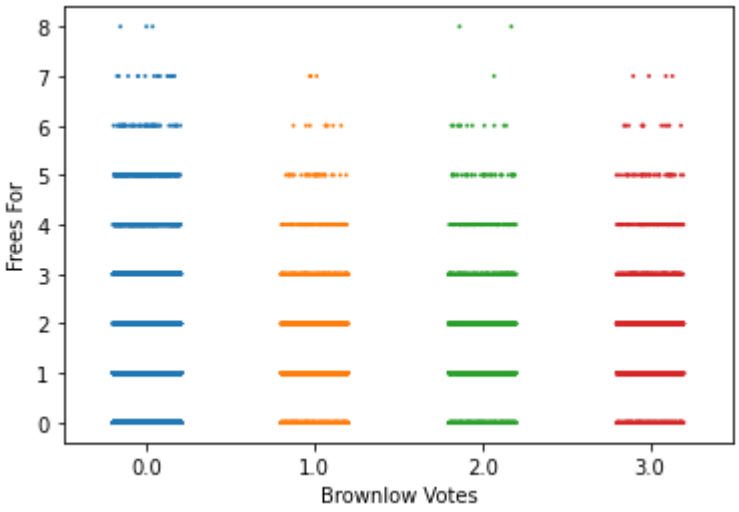

10.0
12.5
15.0
17.5

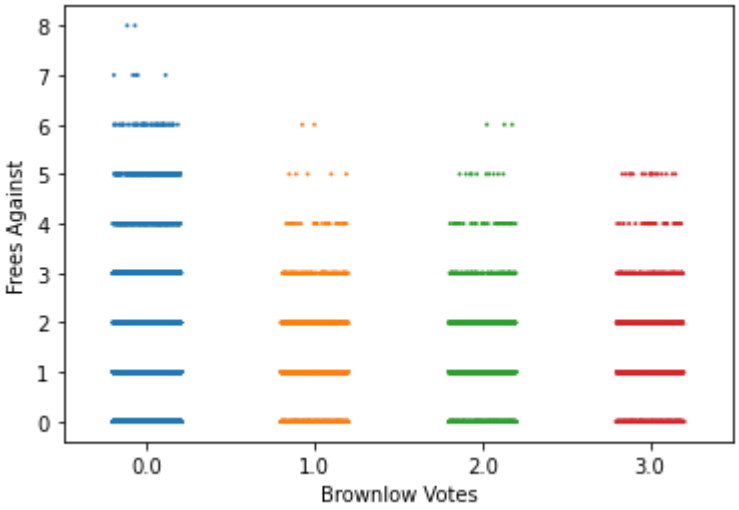

Rebounds
Brownlow Votes
0.0
1.0
2.0
3.0

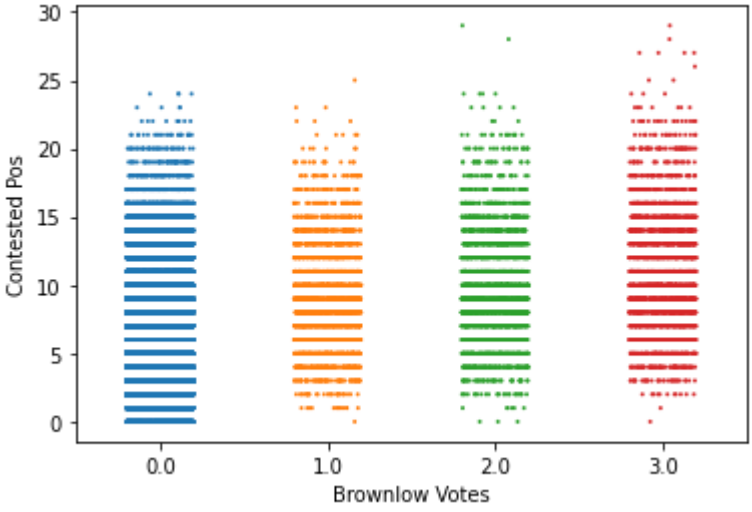

Inside 50s
Brownlow Votes
0.0
1.0
2.0
3.0

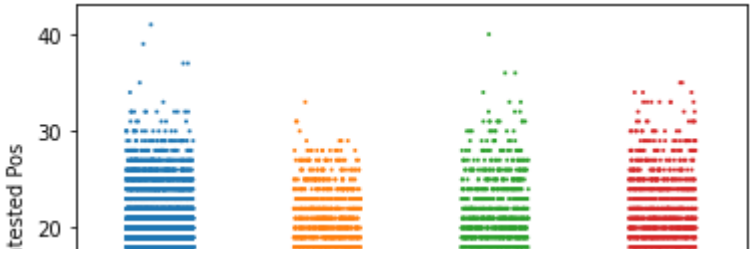

Clearances
Brownlow Votes
0.0
1.0
2.0
3.0

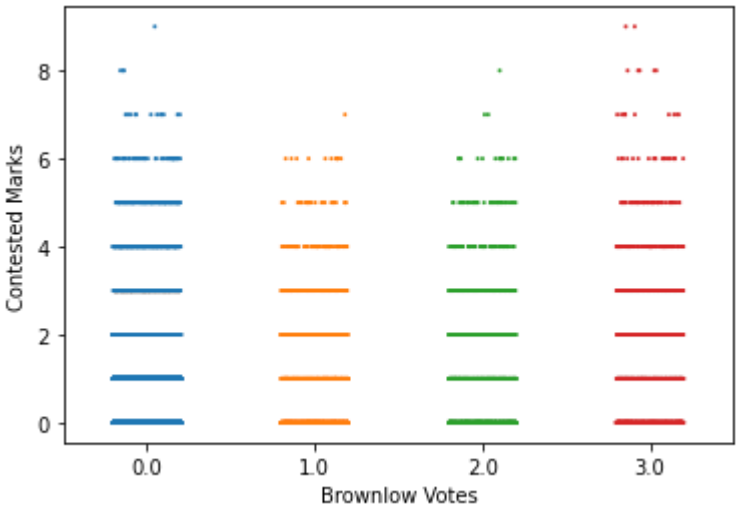

angers

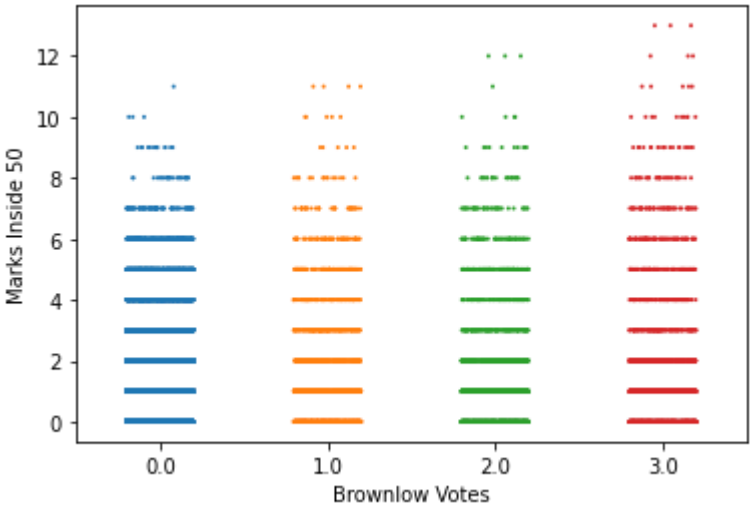

Frees For
Brownlow Votes
0.0
1.0
2.0
3.0
0
1
2
3
4
5
6
7
8

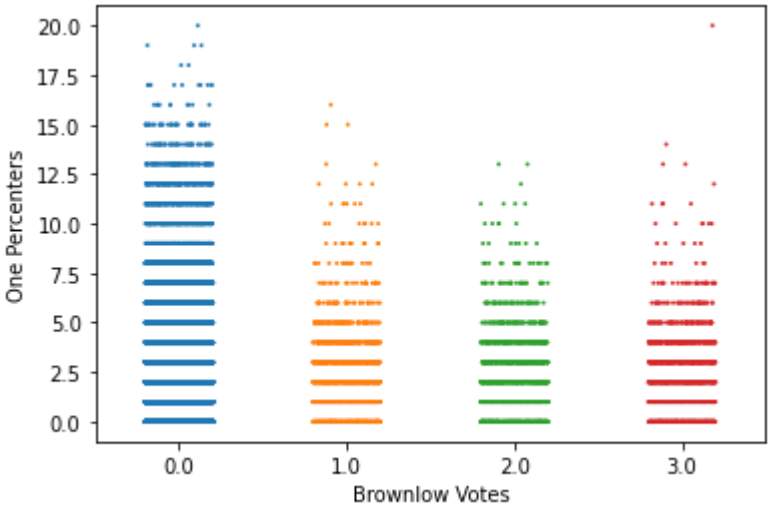

Frees Against
Brownlow Votes
0.0
1.0
2.0
3.0
0
1
2
3
4
5
6
7
8


Contested Pos
Brownlow Votes
0.0
1.0
2.0
3.0
0
5
10
15
20
25
30

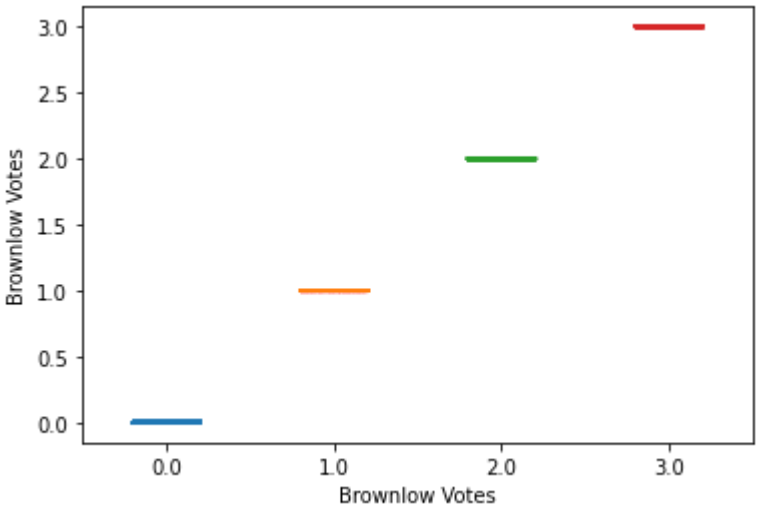

tested Pos
20
30
40

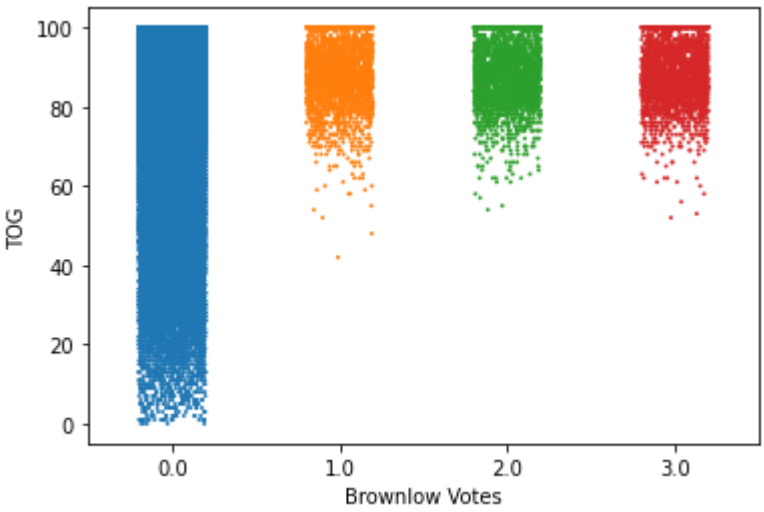

Contested Marks
0
2
4
6
8
0.0
1.0
2.0
3.0
Brownlow Votes

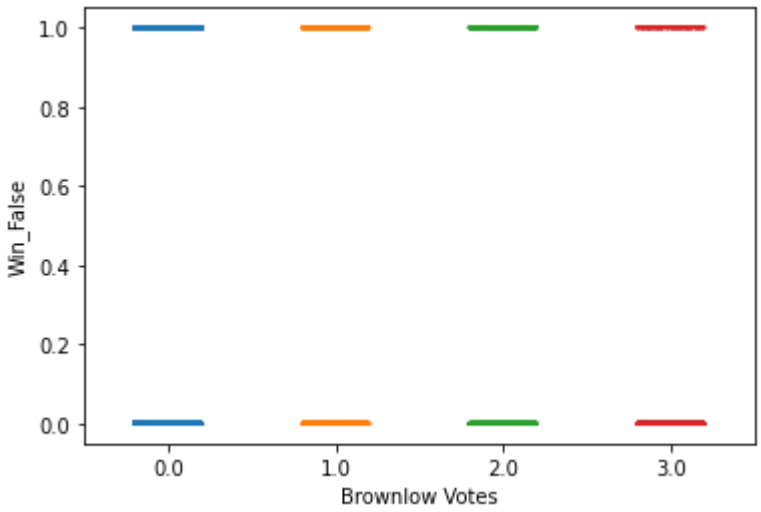

Marks Inside 50
0
2
4
6
8
10
12
0.0
1.0
2.0
3.0
Brownlow Votes

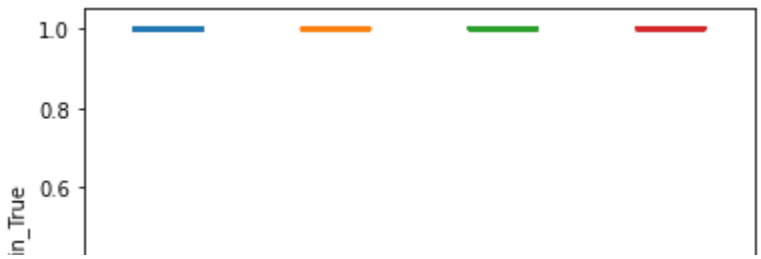

One Percenters
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
0.0
1.0
2.0
3.0
Brownlow Votes


6
8
10


Brownlow Votes
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0.0
1.0
2.0
3.0
Brownlow Votes


TOG
100
80
60
40
20
0
0.0
1.0
2.0
3.0
Brownlow Votes


Win_False
1.0
0.8
0.6
0.4
0.2
0.0
0.0
1.0
2.0
3.0
Brownlow Votes


in_True
1.0
0.8
0.6

It shows that some of the most telling indices are:

- TOG: No voted player plays under 40 minutes
- Goals, Marks inside 50s, Contested Marks, Uncontested Pos, Contested Pos, Inside 50s, Handballs, Kicks, Disposals

We can confirm these with a correlation matrix:

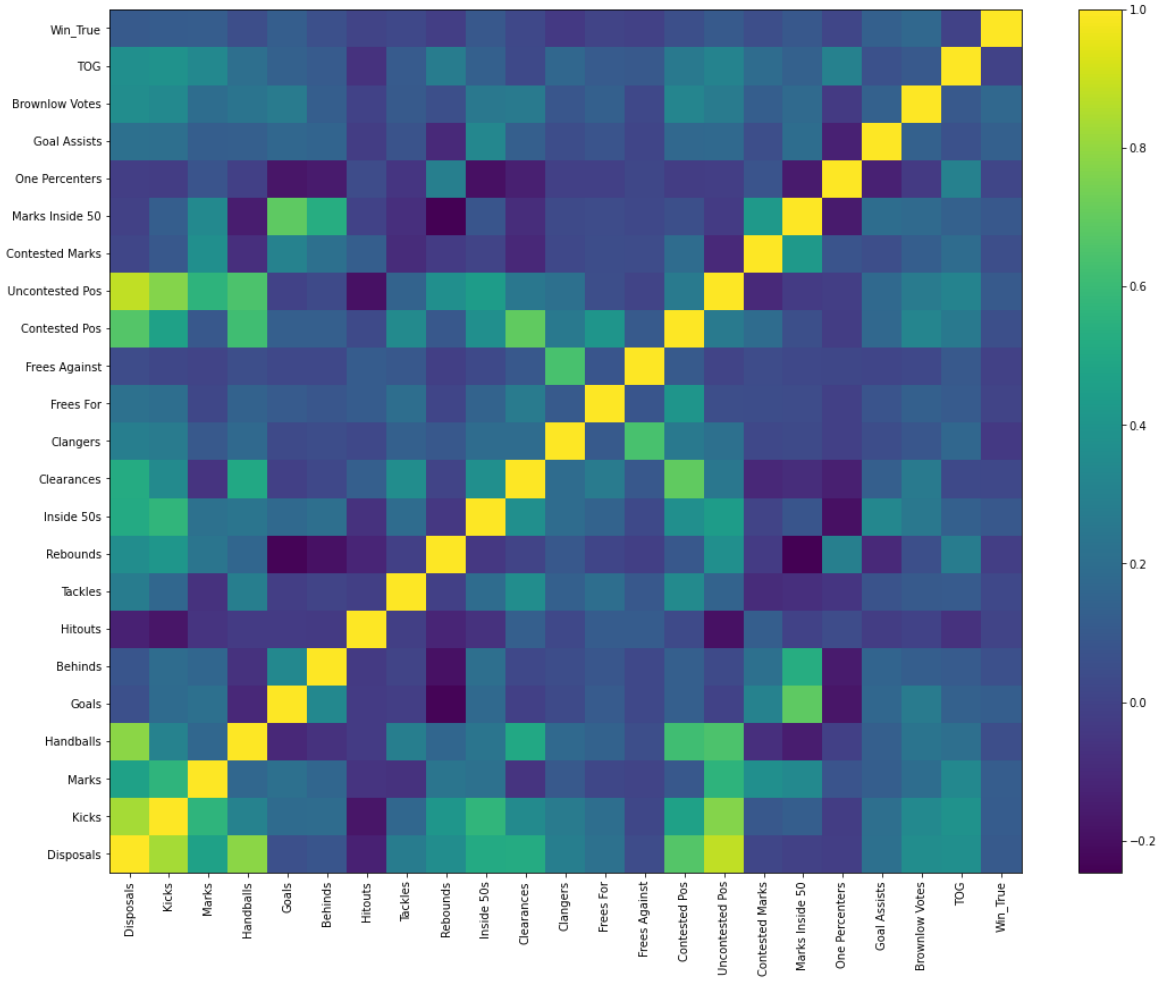
In [16]:
```
train.columns
```

Out[16]:
```
Index(['Name', 'Team', 'Season', 'Round', 'Home Team', 'Away Team',
       'Home Score', 'Away Score', 'Margin', 'Disposals', 'Kicks', 'M
arks',
       'Handballs', 'Goals', 'Behinds', 'Hitouts', 'Tackles', 'Reboun
ds',
       'Inside 50s', 'Clearances', 'Clangers', 'Frees For', 'Frees Ag
ainst',
       'Contested Pos', 'Uncontested Pos', 'Contested Marks',
       'Marks Inside 50', 'One Percenters', 'Goal Assists', 'Brownlow
Votes',
       'TOG', 'Year', 'GameID', 'Win_False', 'Win_True'],
      dtype='object')
```

In [17]:
```
corr = train[['Disposals', 'Kicks', 'Marks',
       'Handballs', 'Goals', 'Behinds', 'Hitouts', 'Tackles', 'Reb
       'Inside 50s', 'Clearances', 'Clangers', 'Frees For', 'Frees
       'Contested Pos', 'Uncontested Pos', 'Contested Marks',
       'Marks Inside 50', 'One Percenters', 'Goal Assists', 'Brown
       'TOG', 'Win_True']].corr()
```

In [18]:
```
1 import numpy as np
2 fig = plt.figure(figsize=(18, 14))
3 c = plt.pcolor(corr)
4 plt.yticks(np.arange(0.5, len(corr.index), 1), corr.index)
5 plt.xticks(np.arange(0.5, len(corr.columns), 1), corr.columns, rot
6 fig.colorbar(c)
```

Out[18]: <matplotlib.colorbar.Colorbar at 0x7f96ba44f250>



3 Approach

It makes more sense to evaluate players in the scope of a game.
We can make an assumption that players are evaluated according to a certain linear formula of the performance indices, then we can normalize the score using softmax to pick the strongest ones.
Formally, a training example looks like this:

Where each row in X corresponds to a player in that game, and the corresponding entry in y is the number of votes he got.

For simplicity, I use `mse` as the loss function, although it seems that there should be a better one.
Because I treat this problem as a regression problem, entries in y will be continuous.
As a final step after the training, I will round these entries to get the final predictions.
For this problem, because the vote tiers are skewed (more zeros than 1, 2, 3), I choose to evaluate recall percentage for each tier rather than overall accuracy.

In [19]:
```
features = ['Disposals', 'Kicks', 'Marks',
       'Handballs', 'Goals', 'Behinds', 'Hitouts', 'Tackles', 'Reb
       'Inside 50s', 'Clearances', 'Clangers', 'Frees For', 'Frees
       'Contested Pos', 'Uncontested Pos', 'Contested Marks',
       'Marks Inside 50', 'One Percenters', 'Goal Assists',
       'TOG', 'Win_False', 'Win_True']
n_features = len(features)

BATCH_SIZE = 32
val_split = .3 # Split 30% for validation from train
```

In [20]:
```
import tensorflow as tf

def make_tfds(data, features=features, split=None):
    """
    For each gameID, stack all the players to get a 44xm matrix
    """

    data_x, data_y = [],[]
    for i, gameid in enumerate(data['GameID'].unique()):
        game = data[data['GameID']==gameid]

        X = np.array(game[features])
        y = np.array(game['Brownlow Votes'])

        data_x.append(X)
        data_y.append(y)

    data_x = np.asarray(data_x) # shape ?, 44, n_features
    data_y = np.asarray(data_y)

    data_x = np.expand_dims(data_x, -1)

    if split != None: # create validation set
        split_point = int(split*data_x.shape[0])
```

```
        val_x = data_x[:split_point,:,:,:]
        val_y = data_y[:split_point,:]
        train_x = data_x[split_point:,:,:,:]
        train_y = data_y[split_point:,]
        return tf.data.Dataset.from_tensor_slices((train_x, train_
                tf.data.Dataset.from_tensor_slices((val_x, val_y))

    return tf.data.Dataset.from_tensor_slices((data_x, data_y))
```

In [21]:
```
train_dataset, val_dataset = make_tfds(train, features, val_split)
test_dataset = make_tfds(test, features)
```

In [22]:
```
train_dataset = train_dataset.batch(BATCH_SIZE)
val_dataset = val_dataset.batch(BATCH_SIZE)
test_dataset = test_dataset.batch(BATCH_SIZE)
```

4 Build and train a model

In [23]:
```
import tensorflow as tf
print(tf.__version__)
from keras.utils import to_categorical
from keras.models import Sequential
from keras.layers import Dense, BatchNormalization, \
            Flatten, Conv2D, Dropout, Lambda
from keras.optimizers import SGD, Adam
```

```
2.2.0-rc2
```

In [35]:
```
def get_model():
    model = Sequential()
    model.add(Conv2D(1, (1, n_features), activation='relu', kernel
    model.add(Conv2D(1, (1, 1), kernel_initializer='he_uniform')),
    model.add(BatchNormalization())
    model.add(Conv2D(1, (1, 1), kernel_initializer='he_uniform')),
    model.add(BatchNormalization())
    model.add(Flatten())
    model.add(Dense(44))
    return model
```

Reasons behind this structure:

- Use conv2D to reduce each row in $44 \times m$ to a single number representing the overall performance of the player.
- Another conv2D to increase the abstraction level, followed by a Batch Norm to avoid exploding/vanishing gradients.
- Repeat.
- Final dense layer allows indirect communication between nodes in conv2D, which may represents the comparision between them.

In [36]:
```
model = get_model()
```

In [37]:
```
model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=.00
              loss='mse')
```

In [38]:
```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 44, 1, 1)          24
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 44, 1, 1)          2
_________________________________________________________________
batch_normalization (BatchNo (None, 44, 1, 1)          4
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 44, 1, 1)          2
_________________________________________________________________
batch_normalization_1 (Batch (None, 44, 1, 1)          4
_________________________________________________________________
flatten (Flatten)            (None, 44)                0
_________________________________________________________________
dense (Dense)                (None, 44)                1980
=================================================================
Total params: 2,016
Trainable params: 2,012
Non-trainable params: 4
_________________________________________________________________
```

In [39]:
```
tf.keras.backend.clear_session()
```

In [40]:
```
model.evaluate(train_dataset) # loss before training
```

```
53/53 [==============================] - 0s 2ms/step - loss: 8055.054
7
```

Out[40]:
```
8055.0546875
```

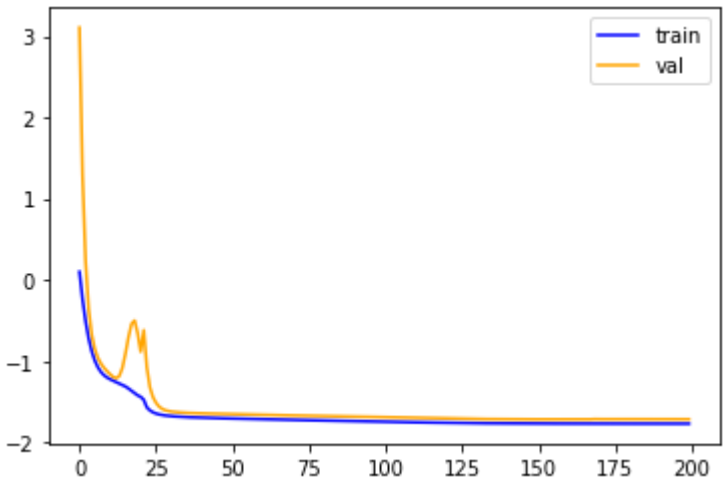
In [41]:
```
history = model.fit(train_dataset, validation_data=val_dataset, ep
```

```
Epoch 1/200
53/53 [==============================] - 0s 3ms/step - loss: 1.1038 -
val_loss: 22.3363
```

In [46]:
```python
import matplotlib.pyplot as plt

def summarize_diagnostics(history):
    # plot log of loss
    plt.plot(np.log(history.history['loss']), color='blue', label=
    plt.plot(np.log(history.history['val_loss']), color='orange',
    # plot accuracy
    plt.legend()
    plt.show()
```

In [47]:
```python
summarize_diagnostics(history)
```



In [44]:
```python
# Performance on val
pred = model.predict(val_dataset)

pred = pred.flatten()

truth = np.array(train['Brownlow Votes'])

def custom_eval(pred, true):

    count = {'1':0, '2':0, '3':0, '0':0}
    total = {'1':0, '2':0, '3':0, '0':0}

    for p,t in zip(list(pred), list(truth)):
        total[str(int(t))] += 1
        if round(p) == t:
            count[str(int(t))] += 1

    return [count[i]/total[i]*100 for i in ('1','2','3','0')]

custom_eval(pred, truth)
```

Out[44]:
```
[51.048951048951054, 16.223776223776223, 7.4125874125874125, 94.64438
001023366]
```

In [45]:
```
# Performance on test
pred = model.predict(test_dataset)
pred = pred.flatten()

truth = np.array(test['Brownlow Votes'])

custom_eval(pred, truth)
```

Out[45]:
```
[55.294117647058826, 24.313725490196077, 8.49673202614379, 93.53419416547106]
```

Summary performance on Test set:

- Recall for `Brownlow=0` entries is 93.5%
- Recall for `1` entries is 55.3%
- Recall for `2` entries is 24.3%
- Recall for `3` entries is 8.5%

5 Space for improvement and experiment

This problem is close to pixel level classification in computer vision, where we feed an image (a matrix) and obtain a matrix of the same dimension with each entry is the class for the corresponding pixel in the original matrix. We can take a look at that problem to see what kind of loss they use.
As far as I know, they often use binary masks in such problems. This may lead to complication.
Another approach is to use a different model.

In [ ]:
```
1
```