Nationwide Application Assessment for Computational Telematics

Part 2

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Now let's import necessary libraries.
numpy for various linear algebra libraries
pandas for convenient file reading as well as dataframe structures that are convenient to work with
matplotlib for various basic plots
geopy for geodesic distances used for calculations in part 1 sklearn, keras (using locally installed tensorflow) for neural network applications

In [135]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from geopy.distance import geodesic
import sys
import sklearn
import keras
from sklearn.model_selection import train_test_split
from keras.models import Model,Sequential
from keras.layers import Dense, Dropout, Input
from keras.callbacks import EarlyStopping
from sklearn.metrics import roc_curve,roc_auc_score
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import confusion_matrix
import xgboost as xgb
```

Part 2 Modeling

In [136]:
```
sim_sum_tot = pd.read_csv(r"C:\Users\JTBar\Documents\Telematics Exercise Files\simulated_summary_total.csv")
```

In [137]:
```
sim_sum_tot.head()
```

Out[137]:

	Vehicle	Days	Distance	HardBrakes	HardAccelerations	NightTime_Pct	VehicleType	Loss
0	1	365	13114	152	56	0.005	SUV	0
1	2	365	18707	147	1	0.010	SUV	0
2	3	365	16659	151	127	0.019	Truck	0
3	4	365	13330	126	147	0.000	SUV	1
4	5	365	22533	10	11	0.001	Truck	0

In [138]:
```
sim_sum_tot.groupby(['VehicleType'])['Loss'].count()
```

Out[138]:
```
VehicleType
Car         9085
Minivan     1520
SUV         7463
Truck      11932
Name: Loss, dtype: int64
```

This dataset contains 30,000 vehicles, of which 4031 have been in a collision. For a further breakdown of how many vehicles have been in a collision by VehicleType:

In [139]:
```
sim_sum_tot.groupby(['VehicleType','Loss'])['Loss'].count()
```

Out[139]:
```
VehicleType  Loss
Car          0        7955
             1        1130
Minivan      0        1365
             1         155
SUV          0        6368
             1        1095
Truck        0       10281
             1        1651
Name: Loss, dtype: int64
```

(4) Is there a statistically significant difference between vehicle types?

If we assume the loss populations are sampled from a binomial distribution with probability given by TotalLossPerType/TotalType a simple z-test can be conducted to determine if the null hypothesis, the distributions being 'sampled' from a similar distribution, can be rejected. For a significance $\alpha = 0.05$ a z-value greater than the critical value of 1.64 means the null hypothesis is rejected and the population proportions are statistically significantly different at the 0.05 significance level. However, there is a nonzero chance that continually looking at distributions will result in a positive effect (The Look-Elsewhere effect) one way to combat this is to divide the significance value youre looking for by the number of unique trials (here 6) and using that critical value. This then is $\alpha = 0.083$ and chances $z_{critical} = 2.64$. However, the choice of p<0.05 rejecting the null hypothesis is a convention and the distinction here is somewhat arbitrary. The conclusions that I draw depend on how liberal we want to be in the definition of statistical significance.

$$z = \frac{p_1 - p_2}{\sqrt{p(1-p)(1/n_1 + 1/n_2)}}$$

In [140]:
```
ProbDict={}
ProbDict['Car']     = [1130.,9085.];
ProbDict['Minivan'] = [155.,1520.] ;
ProbDict['SUV']     = [1095.,7463.];
ProbDict['Truck']   = [1651.,11932.];
```

In [141]:
```
def calculateZ(ProbDict,Vehicle1,Vehicle2):
    #Takes the total sample size of two distributions and number of 'favorabl
e' cases here the Loss and returns a z-test value
    n1=ProbDict[Vehicle1][1]
    x1=ProbDict[Vehicle1][0]
    n2=ProbDict[Vehicle2][1]
    x2=ProbDict[Vehicle2][0]
    p1 = x1/n1
    p2 = x2/n2
    p  = (x1+x2)/(n1+n2)
    z  = np.abs(p1-p2)/np.sqrt(p*(1-p)*(1/n1+1/n2))
    print('z value for %s and %s: %.2f'%(Vehicle1,Vehicle2,z))
    return z
usedKeys=[]
for key in ProbDict:
    usedKeys.append(key)
    for key2 in ProbDict:
        if key !=key2 and key2 not in usedKeys:
            calculateZ(ProbDict,key,key2)
```

```
z value for Car and Minivan: 2.48
z value for Car and SUV: 4.19
z value for Car and Truck: 2.96
z value for Minivan and SUV: 4.59
z value for Minivan and Truck: 3.92
z value for SUV and Truck: 1.62
```

Applying this z test for all possible combinations all combinations can be said to be statistically significant except for the combination of populations of Trucks and SUVs. Including the Look-elsewhere effect also can bring back into statistical insignificance the combination of Cars/Minivans

(5) Are hard brakes and hard accelerations equally important in predicting risks?

In [142]:
```
print("Hard Brakes per Loss Event- Mean: %.2f, Stdev: %.2f, Median: %.2f "%(si
m_sum_tot[sim_sum_tot['Loss']==1]['HardBrakes'].mean(),sim_sum_tot[sim_sum_tot
['Loss']==1]['HardBrakes'].std(), sim_sum_tot[sim_sum_tot['Loss']==1]['HardBra
kes'].median()))
print("Hard Accelerations per Loss Event- Mean: %.2f, Stdev: %.2f, Median: %.2
f "%(sim_sum_tot[sim_sum_tot['Loss']==1]['HardAccelerations'].mean(),sim_sum_t
ot[sim_sum_tot['Loss']==1]['HardAccelerations'].std(),sim_sum_tot[sim_sum_tot[
'Loss']==1]['HardAccelerations'].median()))
```

```
Hard Brakes per Loss Event- Mean: 170.24, Stdev: 495.04, Median: 98.00
Hard Accelerations per Loss Event- Mean: 138.25, Stdev: 534.86, Median: 68.00
```

In [143]:

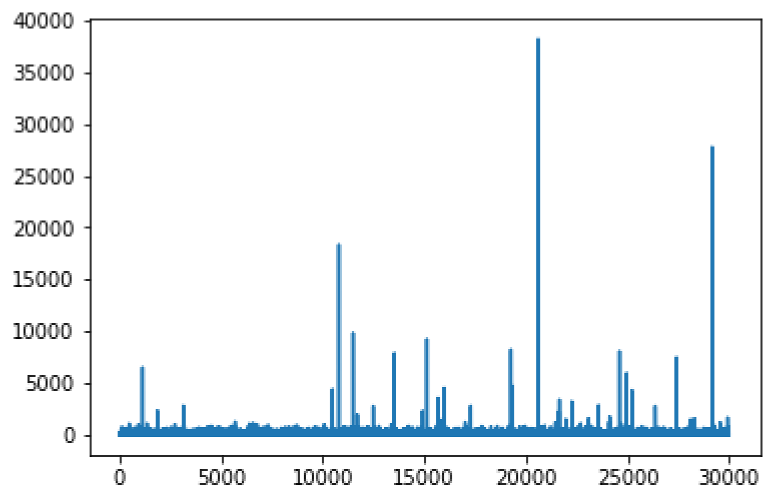
```
print("Hard Brakes per 0 Loss Event- Mean: %.2f, Stdev: %.2f, Median: %.2f "%(sim_sum_tot[sim_sum_tot['Loss']==0]['HardBrakes'].mean(),sim_sum_tot[sim_sum_tot['Loss']==0]['HardBrakes'].std(), sim_sum_tot[sim_sum_tot['Loss']==0]['HardBrakes'].median()))
print("Hard Accelerations per 0 Loss Event- Mean: %.2f, Stdev: %.2f, Median: %.2f "%(sim_sum_tot[sim_sum_tot['Loss']==0]['HardAccelerations'].mean(),sim_sum_tot[sim_sum_tot['Loss']==0]['HardAccelerations'].std(),sim_sum_tot[sim_sum_tot['Loss']==0]['HardAccelerations'].median()))
```

```
Hard Brakes per 0 Loss Event- Mean: 167.44, Stdev: 570.00, Median: 98.00
Hard Accelerations per 0 Loss Event- Mean: 104.53, Stdev: 376.43, Median: 56.
00
```

In [144]:

```
sim_sum_tot[sim_sum_tot['Loss']==0]['HardAccelerations'].plot()
```

Out[144]: <matplotlib.axes._subplots.AxesSubplot at 0x19b81308948>



In [145]:

```
sim_sum_tot[sim_sum_tot['Loss']==1].describe()
```

Out[145]:

	Vehicle	Days	Distance	HardBrakes	HardAccelerations	NightTime_Pct	Lo
count	4031.000000	4031.0	4031.000000	4031.000000	4031.000000	4031.000000	403
mean	15052.420491	365.0	14757.022823	170.241131	138.251054	0.031782	
std	8614.665175	0.0	4514.713625	495.044167	534.856132	0.054822	
min	4.000000	365.0	2488.000000	0.000000	0.000000	0.000000	
25%	7653.500000	365.0	11550.500000	41.000000	25.000000	0.001000	
50%	15071.000000	365.0	14369.000000	98.000000	68.000000	0.008000	
75%	22361.000000	365.0	17477.500000	208.000000	159.000000	0.038000	
max	29981.000000	365.0	34805.000000	16315.000000	24629.000000	0.761000	

In [146]:
```
sim_sum_tot[sim_sum_tot['Loss']==0].describe()
```

Out[146]:

	Vehicle	Days	Distance	HardBrakes	HardAccelerations	NightTime_Pct	
count	25969.000000	25969.0	25969.000000	25969.000000	25969.000000	25969.000000	25!
mean	14992.440718	365.0	13440.090762	167.442951	104.528130	0.029429	
std	8667.612853	0.0	4204.589699	569.999916	376.432155	0.054906	
min	1.000000	365.0	2911.000000	0.000000	0.000000	0.000000	
25%	7477.000000	365.0	10405.000000	39.000000	20.000000	0.001000	
50%	14992.000000	365.0	13039.000000	98.000000	56.000000	0.007000	
75%	22530.000000	365.0	16028.000000	205.000000	129.000000	0.033000	
max	30000.000000	365.0	35159.000000	35639.000000	38221.000000	0.888000	

Model

This model will be employing a densely connected feed forward neural network for event classification Activation functions: rectified linear unit (ReLU) activation function such that the gradients of activation functions will not diminish as you increase the depth of the network sigmoid activation function is applied to the output layer as is standard for classification problems

Loss/Response Function: Binary Cross Entropy will be used to calculate the predicted probability (probability of correct classification based on the input values) Larger predicted probabilites correspond to lower response function values for correctly identified events.

Optimization Function: Adam (Adaptive moment estimation) Optimizer which is the standard efficient optimization function that calulates adaptive learning rates for all parameters in the network. It computes exponentially weighted averages of past gradients and squares of gradients

I'll split up the input dataset into 2 dataframes, X:the useful input values (dropping Loss as it is the classifier, Vehicle which is effectively an index, and Days which is 365 for every row, and y: the truth value of loss prediction

First I'll show an extremely naive approach just taking in the disparate raw datasets before moving onto using the same approach with oversampled minority case events using both the SMOTE and ADASYN oversampling techniques.

In [147]:
```
sim_sum_tot = sim_sum_tot.replace("Car", 0)
sim_sum_tot = sim_sum_tot.replace("SUV", 1)
sim_sum_tot = sim_sum_tot.replace("Truck", 2)
sim_sum_tot = sim_sum_tot.replace("Minivan", 3)

X = sim_sum_tot.drop(['Loss','Vehicle', 'Days'], axis=1)
y = sim_sum_tot['Loss']
```

In [148]:
```
#splitting up the signal and background datasets into training sets, testing s
ets, and validation sets.
#This splits into 64% to be used for training and 16% testing and 16% validati
on
ix = range(y.shape[0])
X_train, X_test, y_train, y_test, ix_train, ix_test = train_test_split(X, y, i
x, train_size=0.8)
X_train, X_val,y_train, y_val,ix_train, ix_val=train_test_split(X_train,y_trai
n,ix_train,test_size=0.2)
```

In [149]:
```
#Neural networks prefer inputs that are similar to each other while at the sam
e time as normally distributed as possible
#sklearn has a variety of scalers that can be used to perform this transformat
ion, here I use RobustScalar
from sklearn.preprocessing import RobustScaler
scaler = RobustScaler()
X_train = scaler.fit_transform(X_train)
X_val = scaler.transform(X_val)
X_test = scaler.transform(X_test)
```

In [150]:
```
#A Function for making various depths and complexities of dense neural network
s
def DNNmodel(Input_shape=(10,), n_hidden=1, n_nodesHidden=20, dropout=0.2, opt
imizer='adam'):
        inputs=Input(shape=Input_shape)
        i=0
        if n_hidden>0:
                hidden=Dense(n_nodesHidden, activation='relu')(inputs)
                hidden=Dropout(dropout)(hidden)
                i+=1
        while i<n_hidden:
                hidden=Dense(n_nodesHidden, activation='relu')(hidden)
                hidden=Dropout(dropout)(hidden)
                i+=1
        outputs = Dense(1,activation='sigmoid')(hidden)
        model = Model(inputs,outputs)
        model.compile(optimizer=optimizer, loss='binary_crossentropy', metrics
=['accuracy'])
        model.summary()
        return model
```

In [151]:
```
model = DNNmodel(Input_shape=(5,),n_hidden=2)
```

```
Model: "model_15"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_15 (InputLayer)        (None, 5)                 0
_________________________________________________________________
dense_56 (Dense)             (None, 20)                120
_________________________________________________________________
dropout_42 (Dropout)         (None, 20)                0
_________________________________________________________________
dense_57 (Dense)             (None, 20)                420
_________________________________________________________________
dropout_43 (Dropout)         (None, 20)                0
_________________________________________________________________
dense_58 (Dense)             (None, 1)                 21
=================================================================
Total params: 561
Trainable params: 561
Non-trainable params: 0
_________________________________________________________________
```

In [152]:
```
model.fit(X_train,y_train,epochs=50,callbacks=[EarlyStopping(verbose=True,pati
ence=10,monitor='val_loss')], validation_data=(X_val, y_val),batch_size=10)
```

```
Train on 19200 samples, validate on 4800 samples
Epoch 1/50
19200/19200 [==============================] - 2s 122us/step - loss: 0.4184 -
accuracy: 0.8645 - val_loss: 0.4054 - val_accuracy: 0.8610
Epoch 2/50
19200/19200 [==============================] - 2s 105us/step - loss: 0.3952 -
accuracy: 0.8670 - val_loss: 0.4040 - val_accuracy: 0.8606
Epoch 3/50
19200/19200 [==============================] - 2s 107us/step - loss: 0.3906 -
accuracy: 0.8672 - val_loss: 0.4031 - val_accuracy: 0.8610
Epoch 4/50
19200/19200 [==============================] - 2s 106us/step - loss: 0.3893 -
accuracy: 0.8672 - val_loss: 0.4022 - val_accuracy: 0.8610
Epoch 5/50
19200/19200 [==============================] - 2s 106us/step - loss: 0.3897 -
accuracy: 0.8672 - val_loss: 0.4022 - val_accuracy: 0.8610
Epoch 6/50
19200/19200 [==============================] - 2s 105us/step - loss: 0.3884 -
accuracy: 0.8672 - val_loss: 0.4014 - val_accuracy: 0.8610
Epoch 7/50
19200/19200 [==============================] - 2s 104us/step - loss: 0.3892 -
accuracy: 0.8671 - val_loss: 0.4002 - val_accuracy: 0.8610
Epoch 8/50
19200/19200 [==============================] - 2s 105us/step - loss: 0.3883 -
accuracy: 0.8672 - val_loss: 0.3993 - val_accuracy: 0.8612
Epoch 9/50
19200/19200 [==============================] - 2s 105us/step - loss: 0.3883 -
accuracy: 0.8672 - val_loss: 0.3999 - val_accuracy: 0.8610
Epoch 10/50
19200/19200 [==============================] - 2s 105us/step - loss: 0.3876 -
accuracy: 0.8671 - val_loss: 0.3999 - val_accuracy: 0.8610
Epoch 11/50
19200/19200 [==============================] - 2s 106us/step - loss: 0.3882 -
accuracy: 0.8672 - val_loss: 0.3989 - val_accuracy: 0.8610
Epoch 12/50
19200/19200 [==============================] - 2s 105us/step - loss: 0.3866 -
accuracy: 0.8672 - val_loss: 0.3992 - val_accuracy: 0.8610
Epoch 13/50
19200/19200 [==============================] - 2s 104us/step - loss: 0.3869 -
accuracy: 0.8672 - val_loss: 0.3988 - val_accuracy: 0.8610
Epoch 14/50
19200/19200 [==============================] - 2s 110us/step - loss: 0.3864 -
accuracy: 0.8671 - val_loss: 0.4002 - val_accuracy: 0.8610
Epoch 15/50
19200/19200 [==============================] - 2s 111us/step - loss: 0.3857 -
accuracy: 0.8672 - val_loss: 0.3997 - val_accuracy: 0.8608
Epoch 16/50
19200/19200 [==============================] - 2s 108us/step - loss: 0.3856 -
accuracy: 0.8672 - val_loss: 0.3993 - val_accuracy: 0.8610
Epoch 17/50
19200/19200 [==============================] - 2s 108us/step - loss: 0.3857 -
accuracy: 0.8672 - val_loss: 0.3997 - val_accuracy: 0.8610
Epoch 18/50
19200/19200 [==============================] - 2s 109us/step - loss: 0.3853 -
accuracy: 0.8672 - val_loss: 0.3993 - val_accuracy: 0.8610
Epoch 19/50
19200/19200 [==============================] - 2s 107us/step - loss: 0.3862 -
```

```
accuracy: 0.8672 - val_loss: 0.3999 - val_accuracy: 0.8610
Epoch 20/50
19200/19200 [==============================] - 2s 107us/step - loss: 0.3856 -
accuracy: 0.8671 - val_loss: 0.3993 - val_accuracy: 0.8610
Epoch 21/50
19200/19200 [==============================] - 2s 107us/step - loss: 0.3851 -
accuracy: 0.8671 - val_loss: 0.3987 - val_accuracy: 0.8610
Epoch 22/50
19200/19200 [==============================] - 2s 105us/step - loss: 0.3856 -
accuracy: 0.8672 - val_loss: 0.3999 - val_accuracy: 0.8610
Epoch 23/50
19200/19200 [==============================] - 2s 106us/step - loss: 0.3856 -
accuracy: 0.8672 - val_loss: 0.3992 - val_accuracy: 0.8610
Epoch 24/50
19200/19200 [==============================] - 2s 105us/step - loss: 0.3854 -
accuracy: 0.8673 - val_loss: 0.3988 - val_accuracy: 0.8610
Epoch 25/50
19200/19200 [==============================] - 2s 106us/step - loss: 0.3854 -
accuracy: 0.8672 - val_loss: 0.3991 - val_accuracy: 0.8610
Epoch 26/50
19200/19200 [==============================] - 2s 105us/step - loss: 0.3849 -
accuracy: 0.8672 - val_loss: 0.3992 - val_accuracy: 0.8610
Epoch 27/50
19200/19200 [==============================] - 2s 106us/step - loss: 0.3848 -
accuracy: 0.8672 - val_loss: 0.3991 - val_accuracy: 0.8610
Epoch 28/50
19200/19200 [==============================] - 2s 105us/step - loss: 0.3855 -
accuracy: 0.8672 - val_loss: 0.3991 - val_accuracy: 0.8610
Epoch 29/50
19200/19200 [==============================] - 2s 106us/step - loss: 0.3853 -
accuracy: 0.8672 - val_loss: 0.3999 - val_accuracy: 0.8610
Epoch 30/50
19200/19200 [==============================] - 2s 106us/step - loss: 0.3851 -
accuracy: 0.8673 - val_loss: 0.3986 - val_accuracy: 0.8610
Epoch 31/50
19200/19200 [==============================] - 2s 107us/step - loss: 0.3845 -
accuracy: 0.8671 - val_loss: 0.3994 - val_accuracy: 0.8610
Epoch 32/50
19200/19200 [==============================] - 2s 104us/step - loss: 0.3851 -
accuracy: 0.8672 - val_loss: 0.4008 - val_accuracy: 0.8610
Epoch 33/50
19200/19200 [==============================] - 2s 105us/step - loss: 0.3848 -
accuracy: 0.8672 - val_loss: 0.3991 - val_accuracy: 0.8610
Epoch 34/50
19200/19200 [==============================] - 2s 103us/step - loss: 0.3843 -
accuracy: 0.8673 - val_loss: 0.3995 - val_accuracy: 0.8610
Epoch 35/50
19200/19200 [==============================] - 2s 104us/step - loss: 0.3852 -
accuracy: 0.8672 - val_loss: 0.3992 - val_accuracy: 0.8610
Epoch 36/50
19200/19200 [==============================] - 2s 109us/step - loss: 0.3842 -
accuracy: 0.8673 - val_loss: 0.3989 - val_accuracy: 0.8610
Epoch 37/50
19200/19200 [==============================] - 2s 107us/step - loss: 0.3846 -
accuracy: 0.8671 - val_loss: 0.3994 - val_accuracy: 0.8610
Epoch 38/50
19200/19200 [==============================] - 2s 105us/step - loss: 0.3840 -
```

```
accuracy: 0.8672 - val_loss: 0.4000 - val_accuracy: 0.8610
Epoch 39/50
19200/19200 [==============================] - 2s 106us/step - loss: 0.3846 -
accuracy: 0.8672 - val_loss: 0.3993 - val_accuracy: 0.8610
Epoch 40/50
19200/19200 [==============================] - 2s 106us/step - loss: 0.3845 -
accuracy: 0.8673 - val_loss: 0.3991 - val_accuracy: 0.8610
Epoch 00040: early stopping
```

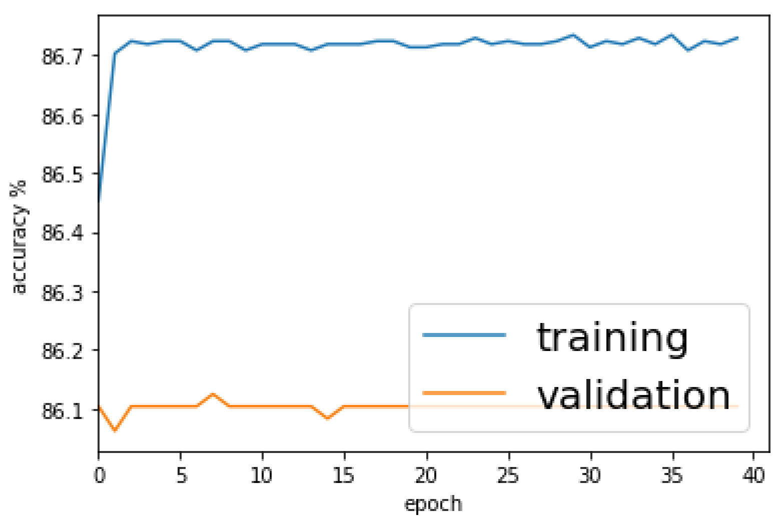
Out[152]: <keras.callbacks.callbacks.History at 0x19b82184fc8>

In [153]:
```
history = model.history.history
print("history keys: ", history.keys())
```

```
history keys:  dict_keys(['val_loss', 'val_accuracy', 'loss', 'accuracy'])
```

In [154]:
```
#Accuracy plot
plt.plot(100 * np.array(history['accuracy']), label='training')
plt.plot(100 * np.array(history['val_accuracy']), label='validation')
plt.xlim(0)
plt.xlabel('epoch')
plt.ylabel('accuracy %')
plt.legend(loc='lower right', fontsize=20)
```

Out[154]: <matplotlib.legend.Legend at 0x19b82504dc8>



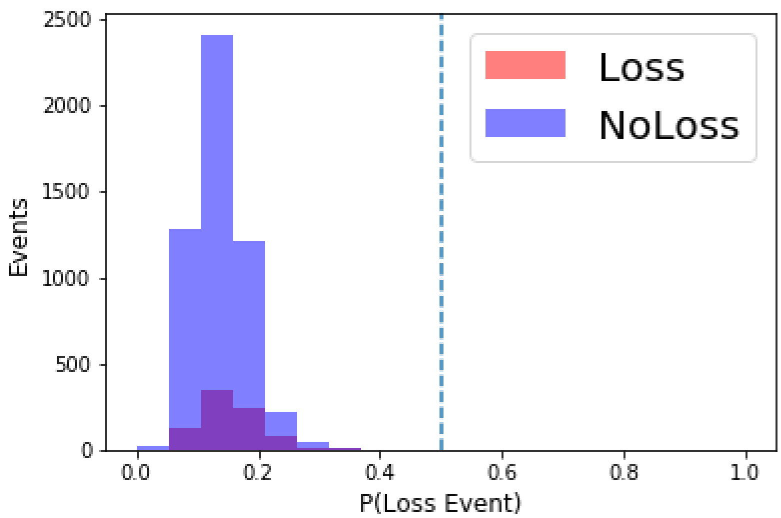
In [155]:
```
yhat = model.predict(X_test, verbose = True, batch_size = 512)
```

```
6000/6000 [==============================] - 0s 52us/step
```

In [156]:
```
yhat_cls = np.argmax(yhat, axis=1)
```

In [157]:
```
bins = np.linspace(0, 1, 20)
_ = plt.hist(yhat[y_test==1], histtype='stepfilled', alpha=0.5, color='red', l
abel=r"Loss", bins=bins)
_ = plt.hist(yhat[y_test==0], histtype='stepfilled', alpha=0.5, color='blue',
label=r'NoLoss', bins=bins)
plt.axvline(x=0.5, linestyle='--')
plt.legend(loc='upper right', fontsize=20)
plt.xlabel('P(Loss Event)', fontsize='large')
plt.ylabel('Events', fontsize='large')
```

Out[157]:
```
Text(0, 0.5, 'Events')
```



In [158]:
```
LossAcc = yhat[y_test==1].round().sum()/y_test.sum()
print("Loss Event Accuracy: %.1f%%" %(LossAcc*100))
```

```
Loss Event Accuracy: 0.0%
```

It is obvious from this that the neural network, at least with the sample given is not sufficient without taking into consideration the disparate nature of the signal/background like events. Even though there is clearly a shape difference in the distributions all events are classified as 'No Loss' because of the large pull from the significant number of 'No Loss' events compared to 'Loss' Events. The network accuracy goes to the percentage of events in the majority case while classifying all signal events incorrectly. To account for this I will preform oversampling

Resampling, NN part 2

Let's try to do some resampling using Adaptive Synthetic Sampling, focuses on data that are hard to learn, fills in more edge cases than the next technique (SMOTE) which fills more linearly between events. [https://imbalanced-learn.readthedocs.io/en/stable/generated/imblearn.over_sampling.ADASYN.html (https://imbalanced-learn.readthedocs.io/en/stable/generated/imblearn.over_sampling.ADASYN.html)](https://imbalanced-learn.readthedocs.io/en/stable/generated/imblearn.over_sampling.ADASYN.html)

In [87]:
```
#Upscale the minority class such that each class has roughly equal representat
ion
from imblearn.over_sampling import ADASYN
adasyn = ADASYN(sampling_strategy="auto")
X_train_adasyn, y_train_adasyn = adasyn.fit_resample(X_train, y_train)
np.bincount(y_train_adasyn)
```

Out[87]:
```
array([16643, 17066], dtype=int64)
```

In [88]:
```
model = DNNmodel(Input_shape=(5,),n_hidden=3);
model.fit(X_train_adasyn,y_train_adasyn,epochs=100,callbacks=[EarlyStopping(verbose=True,patience=20,monitor='val_loss')], validation_data=(X_val, y_val),batch_size=10)
```

```
Model: "model_12"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
input_12 (InputLayer)        (None, 5)                 0         
_________________________________________________________________
dense_44 (Dense)             (None, 20)                120       
_________________________________________________________________
dropout_33 (Dropout)         (None, 20)                0         
_________________________________________________________________
dense_45 (Dense)             (None, 20)                420       
_________________________________________________________________
dropout_34 (Dropout)         (None, 20)                0         
_________________________________________________________________
dense_46 (Dense)             (None, 20)                420       
_________________________________________________________________
dropout_35 (Dropout)         (None, 20)                0         
_________________________________________________________________
dense_47 (Dense)             (None, 1)                 21        
=================================================================
Total params: 981
Trainable params: 981
Non-trainable params: 0
_________________________________________________________________
Train on 33709 samples, validate on 4800 samples
Epoch 1/100
33709/33709 [==============================] - 4s 111us/step - loss: 0.6916 - 
accuracy: 0.5394 - val_loss: 0.7005 - val_accuracy: 0.4908
Epoch 2/100
33709/33709 [==============================] - 3s 103us/step - loss: 0.6868 - 
accuracy: 0.5501 - val_loss: 0.7090 - val_accuracy: 0.5048
Epoch 3/100
33709/33709 [==============================] - 4s 105us/step - loss: 0.6848 - 
accuracy: 0.5558 - val_loss: 0.6963 - val_accuracy: 0.5117
Epoch 4/100
33709/33709 [==============================] - 3s 101us/step - loss: 0.6841 - 
accuracy: 0.5615 - val_loss: 0.7075 - val_accuracy: 0.4998
Epoch 5/100
33709/33709 [==============================] - 3s 102us/step - loss: 0.6829 - 
accuracy: 0.5615 - val_loss: 0.6887 - val_accuracy: 0.5098
Epoch 6/100
33709/33709 [==============================] - 3s 103us/step - loss: 0.6820 - 
accuracy: 0.5625 - val_loss: 0.6879 - val_accuracy: 0.5081
Epoch 7/100
33709/33709 [==============================] - 4s 118us/step - loss: 0.6814 - 
accuracy: 0.5640 - val_loss: 0.7086 - val_accuracy: 0.4840
Epoch 8/100
33709/33709 [==============================] - 4s 132us/step - loss: 0.6807 - 
accuracy: 0.5656 - val_loss: 0.6937 - val_accuracy: 0.5106
Epoch 9/100
33709/33709 [==============================] - 4s 116us/step - loss: 0.6803 - 
accuracy: 0.5686 - val_loss: 0.7089 - val_accuracy: 0.5227
Epoch 10/100
33709/33709 [==============================] - 3s 101us/step - loss: 0.6798 - 
accuracy: 0.5663 - val_loss: 0.6627 - val_accuracy: 0.6158
Epoch 11/100
33709/33709 [==============================] - 4s 116us/step - loss: 0.6800 - 
```

```
accuracy: 0.5673 - val_loss: 0.6946 - val_accuracy: 0.5475
Epoch 12/100
33709/33709 [==============================] - 3s 99us/step - loss: 0.6782 -
accuracy: 0.5695 - val_loss: 0.6664 - val_accuracy: 0.6025
Epoch 13/100
33709/33709 [==============================] - 3s 98us/step - loss: 0.6794 -
accuracy: 0.5709 - val_loss: 0.6668 - val_accuracy: 0.6219
Epoch 14/100
33709/33709 [==============================] - 3s 101us/step - loss: 0.6781 -
accuracy: 0.5694 - val_loss: 0.7003 - val_accuracy: 0.5362
Epoch 15/100
33709/33709 [==============================] - 3s 100us/step - loss: 0.6787 -
accuracy: 0.5709 - val_loss: 0.7060 - val_accuracy: 0.5581
Epoch 16/100
33709/33709 [==============================] - 3s 103us/step - loss: 0.6774 -
accuracy: 0.5739 - val_loss: 0.6679 - val_accuracy: 0.5942
Epoch 17/100
33709/33709 [==============================] - 3s 102us/step - loss: 0.6775 -
accuracy: 0.5758 - val_loss: 0.6853 - val_accuracy: 0.5490
Epoch 18/100
33709/33709 [==============================] - 3s 103us/step - loss: 0.6762 -
accuracy: 0.5751 - val_loss: 0.6858 - val_accuracy: 0.5540
Epoch 19/100
33709/33709 [==============================] - 3s 103us/step - loss: 0.6766 -
accuracy: 0.5759 - val_loss: 0.7008 - val_accuracy: 0.5437
Epoch 20/100
33709/33709 [==============================] - 3s 101us/step - loss: 0.6753 -
accuracy: 0.5737 - val_loss: 0.6863 - val_accuracy: 0.5500
Epoch 21/100
33709/33709 [==============================] - 3s 101us/step - loss: 0.6760 -
accuracy: 0.5742 - val_loss: 0.6751 - val_accuracy: 0.5804
Epoch 22/100
33709/33709 [==============================] - 3s 100us/step - loss: 0.6756 -
accuracy: 0.5755 - val_loss: 0.7007 - val_accuracy: 0.5408
Epoch 23/100
33709/33709 [==============================] - 4s 106us/step - loss: 0.6748 -
accuracy: 0.5784 - val_loss: 0.7159 - val_accuracy: 0.5156
Epoch 24/100
33709/33709 [==============================] - 3s 103us/step - loss: 0.6763 -
accuracy: 0.5758 - val_loss: 0.6906 - val_accuracy: 0.5598
Epoch 25/100
33709/33709 [==============================] - 3s 102us/step - loss: 0.6768 -
accuracy: 0.5726 - val_loss: 0.6785 - val_accuracy: 0.5694
Epoch 26/100
33709/33709 [==============================] - 3s 101us/step - loss: 0.6758 -
accuracy: 0.5758 - val_loss: 0.6845 - val_accuracy: 0.5481
Epoch 27/100
33709/33709 [==============================] - 3s 100us/step - loss: 0.6764 -
accuracy: 0.5759 - val_loss: 0.6971 - val_accuracy: 0.5510
Epoch 28/100
33709/33709 [==============================] - 4s 107us/step - loss: 0.6756 -
accuracy: 0.5768 - val_loss: 0.6980 - val_accuracy: 0.5537
Epoch 29/100
33709/33709 [==============================] - 3s 104us/step - loss: 0.6750 -
accuracy: 0.5772 - val_loss: 0.7004 - val_accuracy: 0.5269
Epoch 30/100
33709/33709 [==============================] - 3s 101us/step - loss: 0.6754 -
```

```
accuracy: 0.5779 - val_loss: 0.7093 - val_accuracy: 0.5421
Epoch 00030: early stopping
```

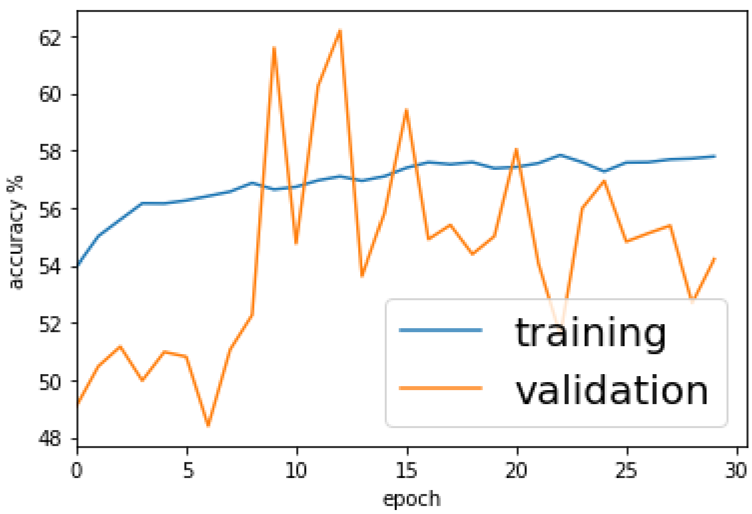
Out[88]: <keras.callbacks.callbacks.History at 0x19bfb37fe08>

In [89]:

```
history = model.history.history
print("history keys: ", history.keys())
#Accuracy plot
plt.plot(100 * np.array(history['accuracy']), label='training')
plt.plot(100 * np.array(history['val_accuracy']), label='validation')
plt.xlim(0)
plt.xlabel('epoch')
plt.ylabel('accuracy %')
plt.legend(loc='lower right', fontsize=20)
```

```
history keys:  dict_keys(['val_loss', 'val_accuracy', 'loss', 'accuracy'])
```

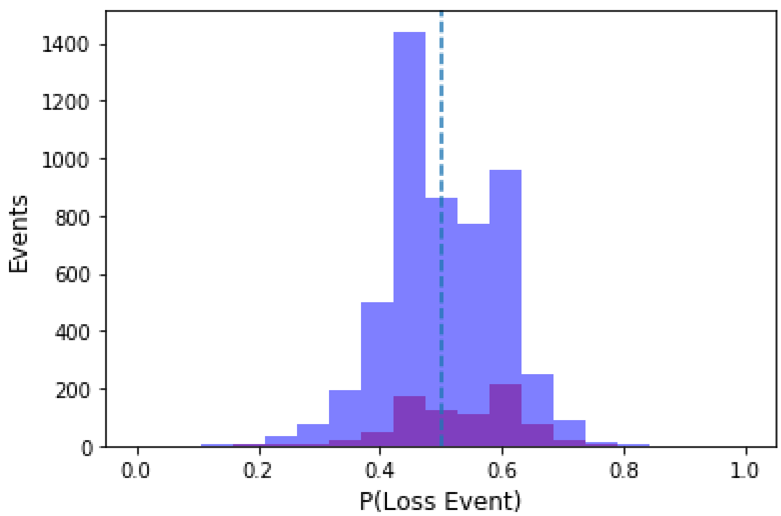
Out[89]: <matplotlib.legend.Legend at 0x19bfc9dbf48>



In [90]:
```
yhat = model.predict(X_test, verbose = True, batch_size = 512)
yhat_cls = np.argmax(yhat, axis=1)
sum(yhat_cls)
bins = np.linspace(0, 1, 20)
_ = plt.hist(yhat[y_test==1], histtype='stepfilled', alpha=0.5, color='red', l
abel=r"Signal", bins=bins)
_ = plt.hist(yhat[y_test==0], histtype='stepfilled', alpha=0.5, color='blue',
label=r'Background', bins=bins)
plt.axvline(x=0.5,linestyle='--')
plt.xlabel('P(Loss Event)', fontsize='large')
plt.ylabel('Events', fontsize='large')
```

```
6000/6000 [==============================] - 0s 44us/step
```

Out[90]: `Text(0, 0.5, 'Events')`



In [91]:
```
print("Loss Events: mean: %.3f, std: %.3f" %(yhat[y_test==1].mean(),yhat[y_tes
t==1].std()))
print("NoLoss Events: mean: %.3f, std: %.3f" %(yhat[y_test==0].mean(),yhat[y_t
est==0].std()))
```

```
Loss Events: mean: 0.535, std: 0.094
NoLoss Events: mean: 0.503, std: 0.092
```

In [92]:
```
LossAcc = yhat[y_test==1].round().sum()/y_test.sum()
print("Loss Event Accuracy: %.1f%%" %(LossAcc*100))
```

```
Loss Event Accuracy: 61.2%
```

Resampling using SMOTE

Synthetic minority oversampling technique (Smote) generates synthetic data that is similar to, but not exactly like the minority class using nearest-neightbors approach to fill in space between neighbors.

In [99]:
```
from imblearn.over_sampling import SMOTE
smote = SMOTE(sampling_strategy="auto")
X_train_smote, y_train_smote = smote.fit_resample(X_train, y_train)
np.bincount(y_train_smote)
```

Out[99]:
```
array([16643, 16643], dtype=int64)
```

In [100]:
```
model = DNNmodel(Input_shape=(5,),n_hidden=3);
model.fit(X_train_smote,y_train_smote,epochs=100,callbacks=[EarlyStopping(verbose=True,patience=20,monitor='val_loss')], validation_data=(X_val, y_val),batch_size=10)
```

```
Model: "model_14"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
input_14 (InputLayer)        (None, 5)                 0         
_________________________________________________________________
dense_52 (Dense)             (None, 20)                120       
_________________________________________________________________
dropout_39 (Dropout)         (None, 20)                0         
_________________________________________________________________
dense_53 (Dense)             (None, 20)                420       
_________________________________________________________________
dropout_40 (Dropout)         (None, 20)                0         
_________________________________________________________________
dense_54 (Dense)             (None, 20)                420       
_________________________________________________________________
dropout_41 (Dropout)         (None, 20)                0         
_________________________________________________________________
dense_55 (Dense)             (None, 1)                 21        
=================================================================
Total params: 981
Trainable params: 981
Non-trainable params: 0
_________________________________________________________________
Train on 33286 samples, validate on 4800 samples
Epoch 1/100
33286/33286 [==============================] - 4s 116us/step - loss: 0.6892 - 
accuracy: 0.5508 - val_loss: 0.6951 - val_accuracy: 0.5235
Epoch 2/100
33286/33286 [==============================] - 4s 106us/step - loss: 0.6828 - 
accuracy: 0.5616 - val_loss: 0.6788 - val_accuracy: 0.5631
Epoch 3/100
33286/33286 [==============================] - 4s 106us/step - loss: 0.6830 - 
accuracy: 0.5649 - val_loss: 0.6618 - val_accuracy: 0.6058
Epoch 4/100
33286/33286 [==============================] - 3s 103us/step - loss: 0.6809 - 
accuracy: 0.5674 - val_loss: 0.6851 - val_accuracy: 0.5702
Epoch 5/100
33286/33286 [==============================] - 3s 103us/step - loss: 0.6804 - 
accuracy: 0.5690 - val_loss: 0.6716 - val_accuracy: 0.5754
Epoch 6/100
33286/33286 [==============================] - 3s 105us/step - loss: 0.6791 - 
accuracy: 0.5714 - val_loss: 0.6953 - val_accuracy: 0.5331
Epoch 7/100
33286/33286 [==============================] - 3s 103us/step - loss: 0.6779 - 
accuracy: 0.5724 - val_loss: 0.6850 - val_accuracy: 0.5369
Epoch 8/100
33286/33286 [==============================] - 3s 103us/step - loss: 0.6792 - 
accuracy: 0.5745 - val_loss: 0.6838 - val_accuracy: 0.5517
Epoch 9/100
33286/33286 [==============================] - 3s 104us/step - loss: 0.6784 - 
accuracy: 0.5749 - val_loss: 0.6714 - val_accuracy: 0.5775
Epoch 10/100
33286/33286 [==============================] - 3s 103us/step - loss: 0.6770 - 
accuracy: 0.5784 - val_loss: 0.6645 - val_accuracy: 0.5925
Epoch 11/100
33286/33286 [==============================] - 3s 103us/step - loss: 0.6760 - 
```

```
accuracy: 0.5787 - val_loss: 0.6794 - val_accuracy: 0.5717
Epoch 12/100
33286/33286 [==============================] - 3s 104us/step - loss: 0.6763 -
accuracy: 0.5771 - val_loss: 0.6724 - val_accuracy: 0.5738
Epoch 13/100
33286/33286 [==============================] - 3s 102us/step - loss: 0.6759 -
accuracy: 0.5777 - val_loss: 0.6974 - val_accuracy: 0.5419
Epoch 14/100
33286/33286 [==============================] - 3s 103us/step - loss: 0.6753 -
accuracy: 0.5759 - val_loss: 0.6897 - val_accuracy: 0.5606
Epoch 15/100
33286/33286 [==============================] - 3s 104us/step - loss: 0.6750 -
accuracy: 0.5776 - val_loss: 0.6942 - val_accuracy: 0.5546
Epoch 16/100
33286/33286 [==============================] - 3s 102us/step - loss: 0.6747 -
accuracy: 0.5790 - val_loss: 0.6757 - val_accuracy: 0.5606
Epoch 17/100
33286/33286 [==============================] - 3s 103us/step - loss: 0.6752 -
accuracy: 0.5802 - val_loss: 0.6746 - val_accuracy: 0.5817
Epoch 18/100
33286/33286 [==============================] - 3s 103us/step - loss: 0.6739 -
accuracy: 0.5805 - val_loss: 0.6684 - val_accuracy: 0.5810
Epoch 19/100
33286/33286 [==============================] - 3s 102us/step - loss: 0.6729 -
accuracy: 0.5822 - val_loss: 0.6651 - val_accuracy: 0.6002
Epoch 20/100
33286/33286 [==============================] - 4s 108us/step - loss: 0.6737 -
accuracy: 0.5810 - val_loss: 0.6740 - val_accuracy: 0.5967
Epoch 21/100
33286/33286 [==============================] - 4s 107us/step - loss: 0.6724 -
accuracy: 0.5827 - val_loss: 0.6816 - val_accuracy: 0.5863
Epoch 22/100
33286/33286 [==============================] - 3s 101us/step - loss: 0.6730 -
accuracy: 0.5806 - val_loss: 0.6693 - val_accuracy: 0.5994
Epoch 23/100
33286/33286 [==============================] - 3s 102us/step - loss: 0.6743 -
accuracy: 0.5829 - val_loss: 0.6756 - val_accuracy: 0.5700
Epoch 00023: early stopping
```

Out[100]:
```
<keras.callbacks.callbacks.History at 0x19bfcbfc588>
```

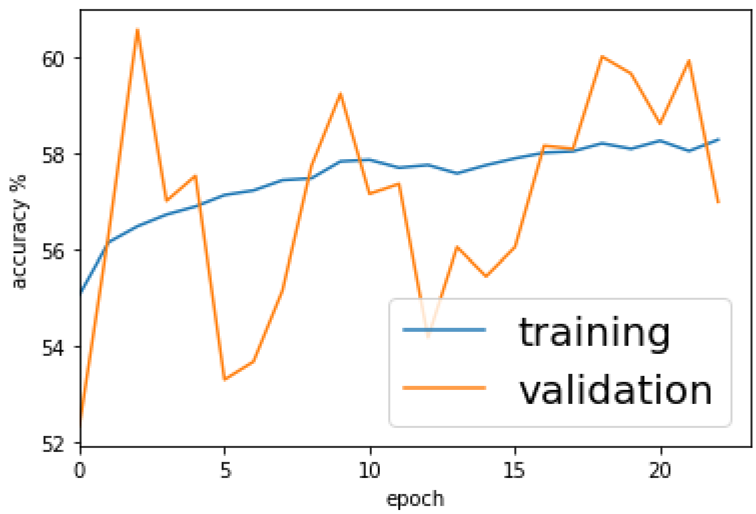
In [101]:

```
history = model.history.history
print("history keys: ", history.keys())
#Accuracy plot
plt.plot(100 * np.array(history['accuracy']), label='training')
plt.plot(100 * np.array(history['val_accuracy']), label='validation')
plt.xlim(0)
plt.xlabel('epoch')
plt.ylabel('accuracy %')
plt.legend(loc='lower right', fontsize=20)
```

```
history keys:  dict_keys(['val_loss', 'val_accuracy', 'loss', 'accuracy'])
```

Out[101]:

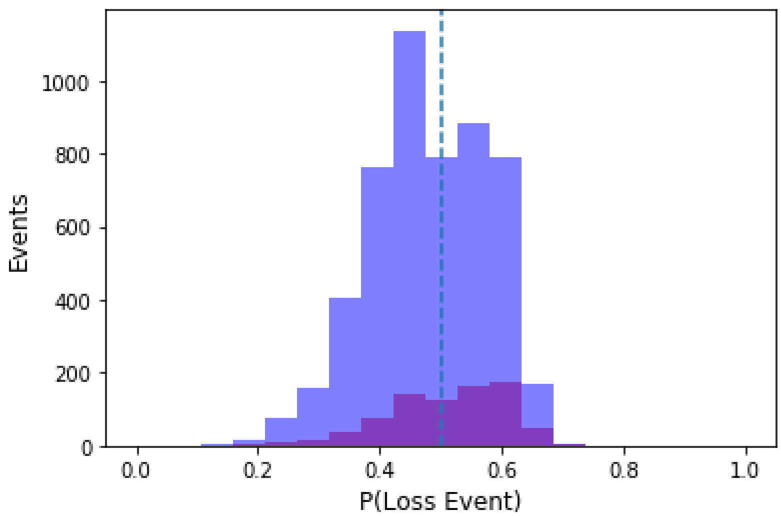
```
<matplotlib.legend.Legend at 0x19bfe356a08>
```



In [102]:
```
yhat = model.predict(X_test, verbose = True, batch_size = 512)
bins = np.linspace(0, 1, 20)
_ = plt.hist(yhat[y_test==1], histtype='stepfilled', alpha=0.5, color='red', label=r"Signal", bins=bins)
_ = plt.hist(yhat[y_test==0], histtype='stepfilled', alpha=0.5, color='blue', label=r'Background', bins=bins)
plt.axvline(x=0.5,linestyle='--')
plt.xlabel('P(Loss Event)', fontsize='large')
plt.ylabel('Events', fontsize='large')
```

```
6000/6000 [==============================] - 0s 50us/step
```

Out[102]:
```
Text(0, 0.5, 'Events')
```



In [103]:
```
print("Loss Events: mean: %.3f, std: %.3f" %(yhat[y_test==1].mean(),yhat[y_test==1].std()))
print("NoLoss Events: mean: %.3f, std: %.3f" %(yhat[y_test==0].mean(),yhat[y_test==0].std()))
```

```
Loss Events: mean: 0.510, std: 0.096
NoLoss Events: mean: 0.480, std: 0.097
```

In [104]:
```
LossAcc = yhat[y_test==1].round().sum()/y_test.sum()
print("Loss Event Accuracy: %.1f%%" %(LossAcc*100))
```

```
Loss Event Accuracy: 55.7%
```

Let's try a BDT instead of a NN, with ADASYN Resampling

Change to XGBoost friendlier format, using all potentially useful columns, dropping Vehicle (an index) and Days (always 365, no chance of separation between loss type events)

In [105]:
```
#splitting up the signal and background datasets into training sets, testing s
ets, and validation sets.
#This splits into 80% to be used for training and 20% testing
X = sim_sum_tot.drop(['Vehicle', 'Days'], axis=1)
y = sim_sum_tot['Loss']
ix = range(y.shape[0])
#X=X.drop('Loss',axis=1)
X_train, X_test, y_train, y_test, ix_train, ix_test = train_test_split(X, y, i
x, train_size=0.8)
#X_train, X_val,y_train, y_val,ix_train, ix_val=train_test_split(X_train,y_tra
in,ix_train,test_size=0.2)
```

In [106]:
```
X.columns
```

Out[106]:
```
Index(['Distance', 'HardBrakes', 'HardAccelerations', 'NightTime_Pct',
       'VehicleType', 'Loss'],
      dtype='object')
```

In [107]:
```
adasyn = ADASYN(sampling_strategy="auto")
X_train_adasyn, y_train_adasyn = adasyn.fit_resample(X_train, y_train)
np.bincount(y_train_adasyn)
```

Out[107]:
```
array([20744, 20434], dtype=int64)
```

In [108]:
```
X_train_adasyn
```

Out[108]:

	Distance	HardBrakes	HardAccelerations	NightTime_Pct	VehicleType	Loss
0	14762	541	12	0.191000	3	0
1	13565	113	54	0.000000	0	0
2	25507	132	119	0.005000	0	0
3	21419	454	78	0.000000	1	0
4	8054	57	129	0.057000	0	0
...	...	...	...	...	...	...
41173	11563	72	73	0.042493	1	1
41174	11577	97	64	0.090249	1	1
41175	11558	48	106	0.078863	0	1
41176	11559	49	106	0.075842	0	1
41177	11575	93	69	0.084200	1	1

41178 rows × 6 columns

In [109]:
```
print('Number of training samples: {}'.format(len(X_train)))
print('Number of testing samples: {}'.format(len(X_test)))
print('ADASYN: Number of training samples: {}'.format(len(X_train_adasyn)))

print('\nNumber of signal events in training set: {}'.format(len(X_train[X_tra
in.Loss == 1])))
print('ADASYN:Number of signal events in training set: {}'.format(len(X_train_
adasyn[X_train_adasyn.Loss == 1])))
print('Number of background events in training set: {}'.format(len(X_train[X_t
rain.Loss == 0])))
print('Fraction signal: {}'.format(len(X_train[X_train.Loss == 1])/(float)(len
(X_train[X_train.Loss == 1]) + len(X_train[X_train.Loss == 0]))))
print('ADASYN: Fraction signal: {}'.format(len(X_train_adasyn[X_train_adasyn.L
oss == 1])/(float)(len(X_train_adasyn[X_train_adasyn.Loss == 1]) + len(X_train
_adasyn[X_train_adasyn.Loss == 0]))))
```

```
Number of training samples: 24000
Number of testing samples: 6000
ADASYN: Number of training samples: 41178

Number of signal events in training set: 3256
ADASYN:Number of signal events in training set: 20434
Number of background events in training set: 20744
Fraction signal: 0.13566666666666666
ADASYN: Fraction signal: 0.49623585409684784
```

In [110]:
```
features = X_train.columns[:-1]  # we skip the last column because it is the L
oss label
features
```

Out[110]:
```
Index(['Distance', 'HardBrakes', 'HardAccelerations', 'NightTime_Pct',
       'VehicleType'],
      dtype='object')
```

In [111]:
```
binary_bdt_param = {
    "learning_rate" : 0.15,
    "max_depth" : 6,
    "colsample_bytree" : 1.0,
    "subsample" : 1.0,
    "n_estimators" : 200,
    "feature_names" : features,
    'objective' : 'binary:logistic' # objective function
}
binary_task_param = {
    "eval_metric" : ["logloss","error"],
    "early_stopping_rounds" : 30,
    "eval_set": [(X_train_adasyn[features],y_train_adasyn),
                 (X_test[features],y_test)]
}

binary_bdt = xgb.XGBClassifier(**binary_bdt_param)
binary_bdt.fit(X_train_adasyn[features], y_train_adasyn,
               verbose=False, **binary_task_param)
```

```
[20:07:03] WARNING: C:\Users\Administrator\workspace\xgboost-win64_release_1.
1.0\src\learner.cc:480:
Parameters: { feature_names } might not be used.

  This may not be accurate due to some parameters are only used in language b
indings but
  passed down to XGBoost core.  Or some parameters are not used but slip thro
ugh this
  verification. Please open an issue if you find above cases.
```

Out[111]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1.0,
              feature_names=Index(['Distance', 'HardBrakes', 'HardAcceleratio
ns', 'NightTime_Pct',
       'VehicleType'],
      dtype='object'),
              gamma=0, gpu_id=-1, importance_type='gain',
              interaction_constraints='', learning_rate=0.15, max_delta_step=
0,
              max_depth=6, min_child_weight=1, missing=nan,
              monotone_constraints='()', n_estimators=200, n_jobs=0,
              num_parallel_tree=1, random_state=0, reg_alpha=0, reg_lambda=1,
              scale_pos_weight=1, subsample=1.0, tree_method='exact',
              validate_parameters=1, verbosity=None)
```

In [112]:
```
evaluated_df = X_test.copy()
evaluated_df["binary_prob"] = binary_bdt.predict_proba(X_test[features])[:,1]
print(binary_bdt.score(X_test[features],y_test))

binary_bdt.predict_proba(X_test[features])[:,1].round().sum()
```

```
0.808
```

Out[112]:
```
547.0
```

In [113]:
```
y_pred = binary_bdt.predict(X_test[features])
y_pred.sum()
```

Out[113]:
```
547
```

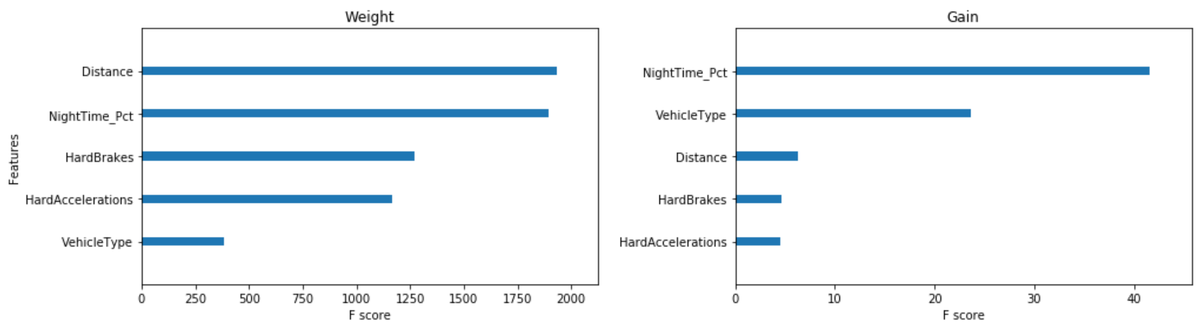
In [114]:
```
binary_bdt.predict(X_test[features])
```

Out[114]:
```
array([1, 0, 1, ..., 0, 0, 0], dtype=int64)
```

In [115]:
```
from sklearn.metrics import accuracy_score
from sklearn.feature_selection import SelectFromModel

predictions = binary_bdt.predict(X_test[features])
accuracy = accuracy_score(y_test, predictions)
print("Accuracy: %.2f%%" % (accuracy * 100.0))
thresholds = np.sort(binary_bdt.feature_importances_)
for thresh in thresholds:
    # select features using threshold
    selection = SelectFromModel(binary_bdt, threshold=thresh, prefit=True)
    select_X_train = selection.transform(X_train_adasyn[features])
    # train model
    selection_model = xgb.XGBClassifier()
    selection_model.fit(select_X_train, y_train_adasyn)
    # eval model
    select_X_test = selection.transform(X_test[features])
    predictions = selection_model.predict(select_X_test)
    accuracy = accuracy_score(y_test, predictions)
    print("Loss Event Accuracy: %.2f%%"%(predictions[y_test==1].sum()/y_test.s
um()*100.))
    print("Thresh=%.3f, n=%d, Accuracy: %.2f%%" % (thresh, select_X_train.shap
e[1], accuracy*100.0))
```

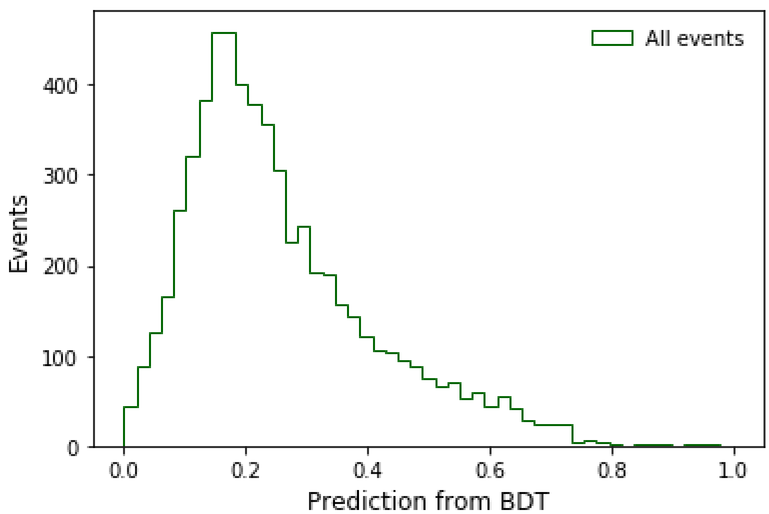
```
Accuracy: 80.80%
Loss Event Accuracy: 10.32%
Thresh=0.056, n=5, Accuracy: 80.98%
Loss Event Accuracy: 10.32%
Thresh=0.057, n=4, Accuracy: 81.93%
Loss Event Accuracy: 9.16%
Thresh=0.078, n=3, Accuracy: 82.18%
Loss Event Accuracy: 4.77%
Thresh=0.292, n=2, Accuracy: 83.87%
Loss Event Accuracy: 2.97%
Thresh=0.515, n=1, Accuracy: 83.83%
```

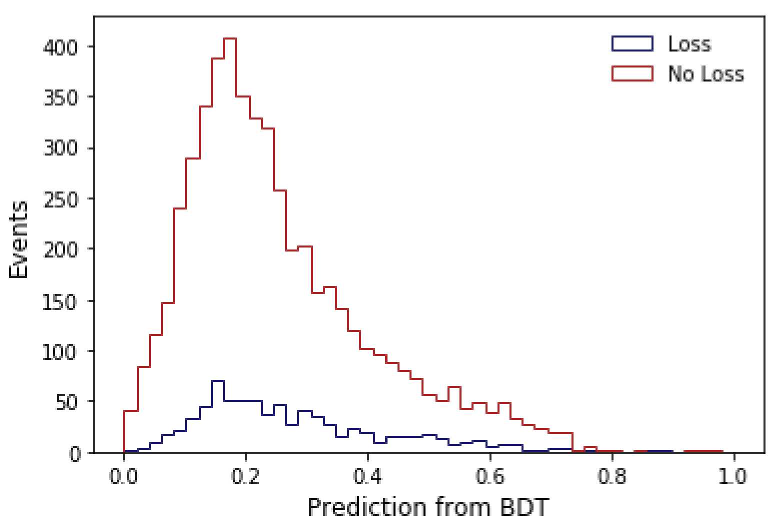
In [116]:
```
fig, ax_enum = plt.subplots(1,2, figsize=(16,4))
xgb.plot_importance(binary_bdt, importance_type="weight", ax=ax_enum[0], title
="Weight",show_values=False, grid=False)
xgb.plot_importance(binary_bdt, importance_type="gain", ax=ax_enum[1], title=
"Gain", show_values=False, grid=False)
plt.ylabel("")
plt.sca(ax_enum[1])
plt.ylabel("")
plt.subplots_adjust(wspace=0.3)
```



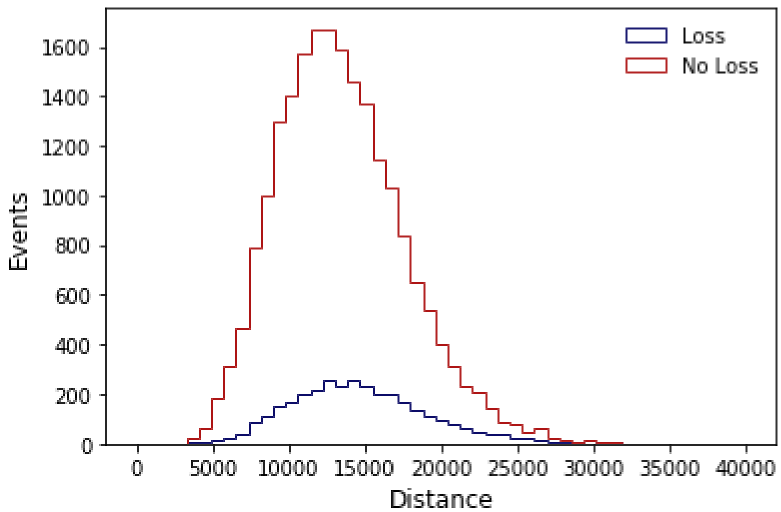
importance_type=Gain is how useful is the variable in terms of separation where importance_type=Weight is how frequently splitting on the variable occurs

In [117]:
```
# plot all predictions (both signal and background)
predictions = binary_bdt.predict_proba(X_test[features])[:,1]
plt.figure();
plt.hist(predictions,bins=np.linspace(0,1,50),histtype='step',color='darkgree
n',label='All events');
# make the plot readable
plt.xlabel('Prediction from BDT',fontsize=12);
plt.ylabel('Events',fontsize=12);
plt.legend(frameon=False);

# plot signal and background separately
plt.figure();
plt.hist(binary_bdt.predict_proba(X_test[features][y_test==1])[:,1],bins=np.li
nspace(0,1,50),
         histtype='step',color='midnightblue',label='Loss');
plt.hist(binary_bdt.predict_proba(X_test[features][y_test==0])[:,1],bins=np.li
nspace(0,1,50),
         histtype='step',color='firebrick',label='No Loss');
# make the plot readable
plt.xlabel('Prediction from BDT',fontsize=12);
plt.ylabel('Events',fontsize=12);
plt.legend(frameon=False);
```

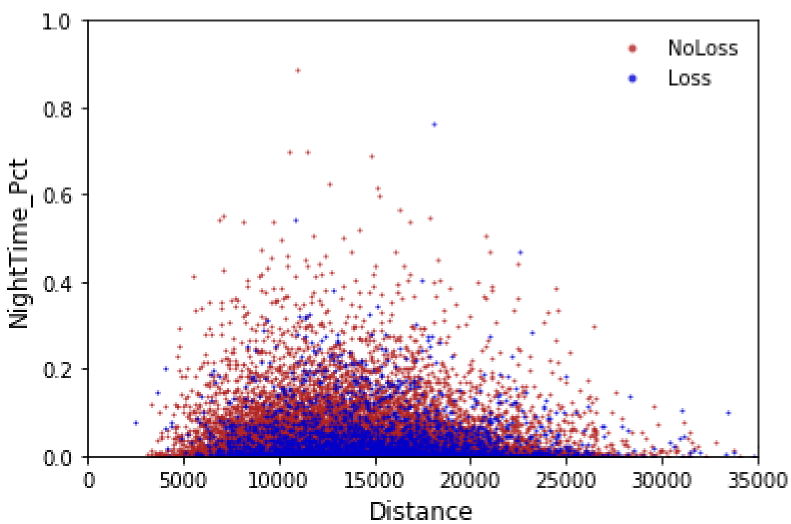




In [118]:
```
plt.figure();
plt.hist(X_train.Distance[X_train.Loss == 1],bins=np.linspace(0,40000,50),
         histtype='step',color='midnightblue',label='Loss');
plt.hist(X_train.Distance[X_train.Loss == 0],bins=np.linspace(0,40000,50),
         histtype='step',color='firebrick',label='No Loss');

plt.xlabel('Distance',fontsize=12);
plt.ylabel('Events',fontsize=12);
plt.legend(frameon=False);
```



In [119]:
```
plt.figure();
#plt.plot(X_train_adasyn.Distance[X_train_adasyn.Loss == 0],X_train_adasyn.NightTime_Pct[X_train_adasyn.Loss == 0],
#         'o',markersize=2,color='firebrick',markeredgewidth=0,alpha=0.8,label='NoLoss');
#plt.plot(X_train_adasyn.Distance[X_train_adasyn.Loss == 1],X_train_adasyn.NightTime_Pct[X_train_adasyn.Loss == 1],
#         'o',markersize=2,color='mediumblue',markeredgewidth=0,alpha=0.8,label='Loss');

plt.plot(X_train.Distance[X_train.Loss == 0],X_train.NightTime_Pct[X_train.Loss == 0],
         'o',markersize=2,color='firebrick',markeredgewidth=0,alpha=0.8,label='NoLoss');
plt.plot(X_train.Distance[X_train.Loss == 1],X_train.NightTime_Pct[X_train.Loss == 1],
         'o',markersize=2,color='mediumblue',markeredgewidth=0,alpha=0.8,label='Loss');

plt.xlim(0,35000);
plt.ylim(0.0,1);
#plt.yscale('log')
plt.xlabel('Distance',fontsize=12);
plt.ylabel('NightTime_Pct',fontsize=12);
plt.legend(frameon=False,numpoints=1,markerscale=2);
```



BDT with SMOTE resampling

Change to XGBoost friendlier format, using all potentially useful columns, dropping Vehicle (an index) and Days (always 365, no chance of separation between loss type events)

In [120]:
```
#splitting up the signal and background datasets into training sets, testing s
ets, and validation sets.
#This splits into 80% to be used for training and 20% testing
X = sim_sum_tot.drop(['Vehicle', 'Days'], axis=1)
y = sim_sum_tot['Loss']
ix = range(y.shape[0])
#X=X.drop('Loss',axis=1)
X_train, X_test, y_train, y_test, ix_train, ix_test = train_test_split(X, y, i
x, train_size=0.8)
#X_train, X_val,y_train, y_val,ix_train, ix_val=train_test_split(X_train,y_tra
in,ix_train,test_size=0.2)
```

In [121]:
```
X.columns
```

Out[121]:
```
Index(['Distance', 'HardBrakes', 'HardAccelerations', 'NightTime_Pct',
       'VehicleType', 'Loss'],
      dtype='object')
```

In [122]:
```
adasyn = SMOTE(sampling_strategy="auto")
X_train_smote, y_train_smote = smote.fit_resample(X_train, y_train)
np.bincount(y_train_smote)
```

Out[122]:
```
array([20796, 20796], dtype=int64)
```

In [123]:
```
X_train_smote
```

Out[123]:

	Distance	HardBrakes	HardAccelerations	NightTime_Pct	VehicleType	Loss
0	15595	446	16	0.017000	1	1
1	17220	207	155	0.009000	2	0
2	14428	167	2	0.003000	2	0
3	7961	103	1	0.056000	3	0
4	13196	1	10	0.024000	1	0
...	...	...	...	...	...	...
41587	11544	63	142	0.159022	2	1
41588	19066	288	188	0.022176	2	1
41589	14291	77	38	0.078869	2	1
41590	15489	77	386	0.013539	0	1
41591	16749	308	28	0.029469	1	1

41592 rows × 6 columns

In [124]:
```
print('Number of training samples: {}'.format(len(X_train)))
print('Number of testing samples: {}'.format(len(X_test)))
print('SMOTE: Number of training samples: {}'.format(len(X_train_smote)))

print('\nNumber of signal events in training set: {}'.format(len(X_train[X_tra
in.Loss == 1])))
print('SMOTE:Number of signal events in training set: {}'.format(len(X_train_s
mote[X_train_smote.Loss == 1])))
print('Number of background events in training set: {}'.format(len(X_train[X_t
rain.Loss == 0])))
print('Fraction signal: {}'.format(len(X_train[X_train.Loss == 1])/(float)(len
(X_train[X_train.Loss == 1]) + len(X_train[X_train.Loss == 0]))))
print('SMOTE: Fraction signal: {}'.format(len(X_train_smote[X_train_smote.Loss
== 1])/(float)(len(X_train_adasyn[X_train_smote.Loss == 1]) + len(X_train_smot
e[X_train_smote.Loss == 0]))))
```

```
Number of training samples: 24000
Number of testing samples: 6000
SMOTE: Number of training samples: 41592

Number of signal events in training set: 3204
SMOTE:Number of signal events in training set: 20796
Number of background events in training set: 20796
Fraction signal: 0.1335
SMOTE: Fraction signal: 0.5050269561416291
```

```
D:\ProgramData\Anaconda3\lib\site-packages\ipykernel_launcher.py:9: UserWarni
ng: Boolean Series key will be reindexed to match DataFrame index.
  if __name__ == '__main__':
```

In [125]:
```
features = X_train.columns[:-1]  # we skip the last column because it is the L
oss label
features
```

Out[125]:
```
Index(['Distance', 'HardBrakes', 'HardAccelerations', 'NightTime_Pct',
       'VehicleType'],
      dtype='object')
```

In [126]:
```
binary_bdt_param = {
    "learning_rate" : 0.15,
    "max_depth" :6,
    "colsample_bytree" : 1.0,
    "subsample" : 1.0,
    "n_estimators" : 200,
    "feature_names" : features,
    'objective' : 'binary:logistic' # objective function
}
binary_task_param = {
    "eval_metric" : ["logloss","error"],
    "early_stopping_rounds" : 30,
    "eval_set": [(X_train_adasyn[features],y_train_adasyn),
                 (X_test[features],y_test)]
}

binary_bdt = xgb.XGBClassifier(**binary_bdt_param)
binary_bdt.fit(X_train_smote[features], y_train_smote,
              verbose=False, **binary_task_param)
```

```
[20:07:10] WARNING: C:\Users\Administrator\workspace\xgboost-win64_release_1.
1.0\src\learner.cc:480:
Parameters: { feature_names } might not be used.

  This may not be accurate due to some parameters are only used in language b
indings but
  passed down to XGBoost core.  Or some parameters are not used but slip thro
ugh this
  verification. Please open an issue if you find above cases.
```

Out[126]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1.0,
              feature_names=Index(['Distance', 'HardBrakes', 'HardAcceleratio
ns', 'NightTime_Pct',
       'VehicleType'],
      dtype='object'),
              gamma=0, gpu_id=-1, importance_type='gain',
              interaction_constraints='', learning_rate=0.15, max_delta_step=
0,
              max_depth=6, min_child_weight=1, missing=nan,
              monotone_constraints='()', n_estimators=200, n_jobs=0,
              num_parallel_tree=1, random_state=0, reg_alpha=0, reg_lambda=1,
              scale_pos_weight=1, subsample=1.0, tree_method='exact',
              validate_parameters=1, verbosity=None)
```

In [127]:
```
evaluated_df = X_test.copy()
evaluated_df["binary_prob"] = binary_bdt.predict_proba(X_test[features])[:,1]
print(binary_bdt.score(X_test[features],y_test))

binary_bdt.predict_proba(X_test[features])[:,1].round().sum()
```

```
0.8045
```

Out[127]:
```
520.0
```

In [128]:
```
y_pred = binary_bdt.predict(X_test[features])
y_pred.sum()
```

Out[128]:
```
520
```

In [129]:
```
binary_bdt.predict(X_test[features])
```

Out[129]:
```
array([0, 0, 0, ..., 0, 0, 0], dtype=int64)
```

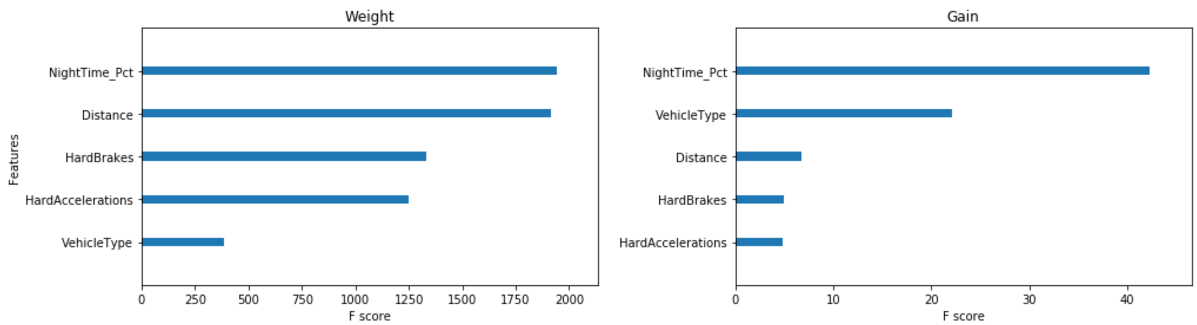
In [130]:
```
from sklearn.metrics import accuracy_score
from sklearn.feature_selection import SelectFromModel

predictions = binary_bdt.predict(X_test[features])
accuracy = accuracy_score(y_test, predictions)
print("Accuracy: %.2f%%" % (accuracy * 100.0))
thresholds = np.sort(binary_bdt.feature_importances_)
for thresh in thresholds:
    # select features using threshold
    selection = SelectFromModel(binary_bdt, threshold=thresh, prefit=True)
    select_X_train = selection.transform(X_train_smote[features])
    # train model
    selection_model = xgb.XGBClassifier()
    selection_model.fit(select_X_train, y_train_smote)
    # eval model
    select_X_test = selection.transform(X_test[features])
    predictions = selection_model.predict(select_X_test)
    accuracy = accuracy_score(y_test, predictions)
    print("Loss Event Accuracy: %.2f%%"%(predictions[y_test==1].sum()/y_test.s
um()*100.))
    print("Thresh=%.3f, n=%d, Accuracy: %.2f%%" % (thresh, select_X_train.shap
e[1], accuracy*100.0))
```

```
Accuracy: 80.45%
Loss Event Accuracy: 12.58%
Thresh=0.060, n=5, Accuracy: 80.30%
Loss Event Accuracy: 10.28%
Thresh=0.062, n=4, Accuracy: 81.22%
Loss Event Accuracy: 10.88%
Thresh=0.084, n=3, Accuracy: 80.97%
Loss Event Accuracy: 4.35%
Thresh=0.273, n=2, Accuracy: 83.18%
Loss Event Accuracy: 3.87%
Thresh=0.521, n=1, Accuracy: 83.95%
```

In [131]:
```
predictions[y_test==1].sum()/y_test.sum()
y_pred[y_test==1].sum()/y_test.sum()
```

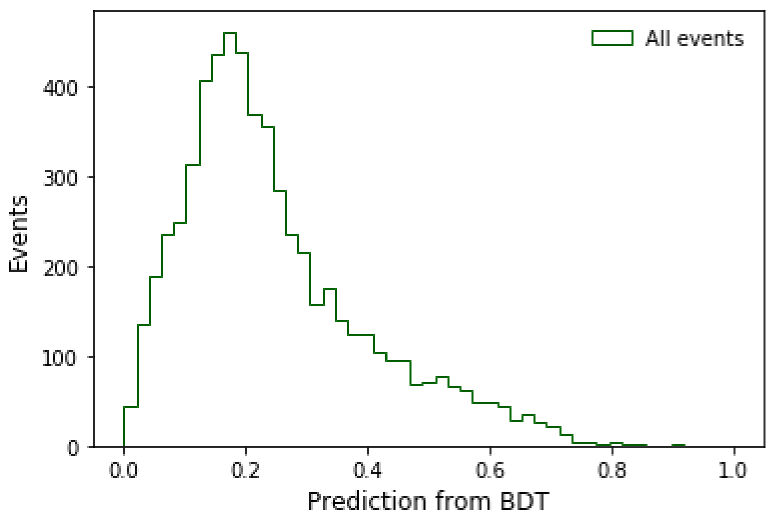
Out[131]: 0.10519951632406288

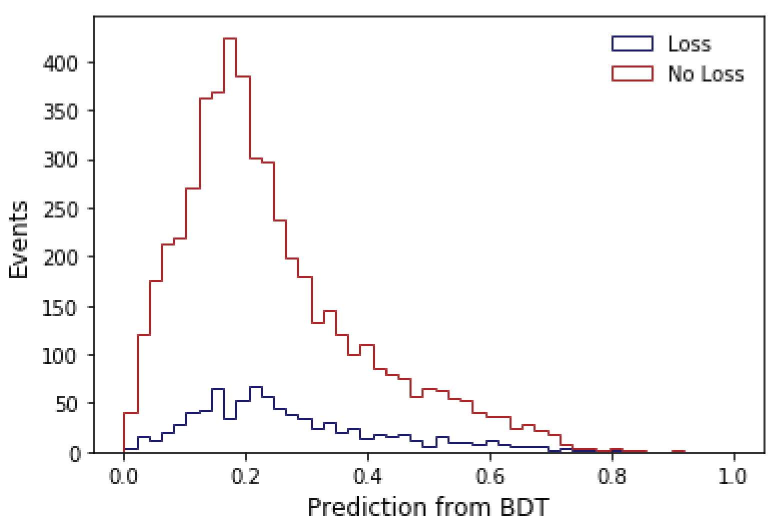
In [132]:
```
fig, ax_enum = plt.subplots(1,2, figsize=(16,4))
xgb.plot_importance(binary_bdt, importance_type="weight", ax=ax_enum[0], title
="Weight",show_values=False, grid=False)
xgb.plot_importance(binary_bdt, importance_type="gain", ax=ax_enum[1], title=
"Gain", show_values=False, grid=False)
plt.ylabel("")
plt.sca(ax_enum[1])
plt.ylabel("")
plt.subplots_adjust(wspace=0.3)
```



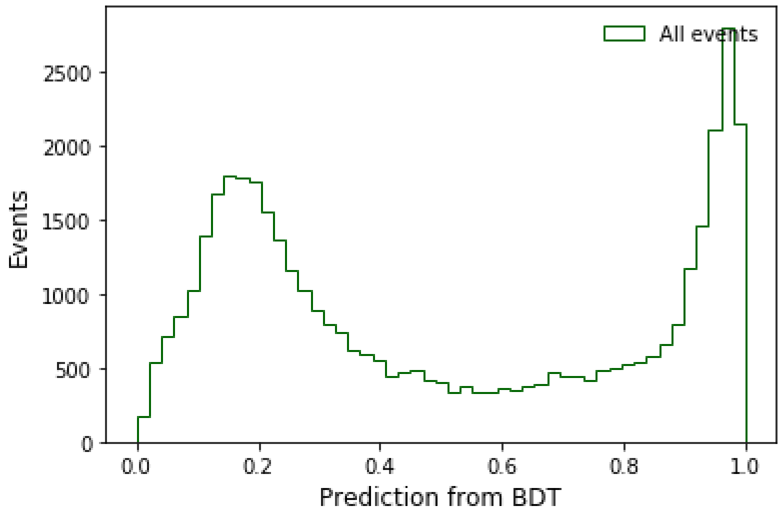
importance_type=Gain is how useful is the variable in terms of separation where importance_type=Weight is how frequently splitting on the variable occurs

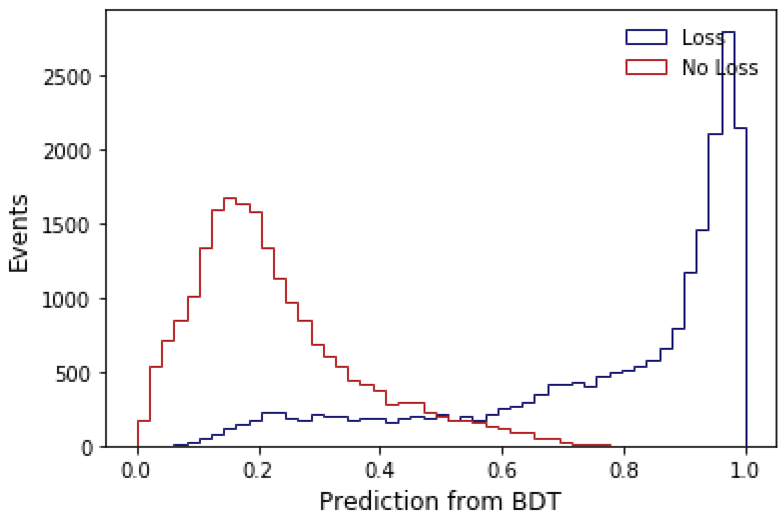
In [133]:
```
# plot all predictions (both signal and background)
predictions = binary_bdt.predict_proba(X_test[features])[:,1]
plt.figure();
plt.hist(predictions,bins=np.linspace(0,1,50),histtype='step',color='darkgree
n',label='All events');
# make the plot readable
plt.xlabel('Prediction from BDT',fontsize=12);
plt.ylabel('Events',fontsize=12);
plt.legend(frameon=False);

# plot signal and background separately
plt.figure();
plt.hist(binary_bdt.predict_proba(X_test[features][y_test==1])[:,1],bins=np.li
nspace(0,1,50),
         histtype='step',color='midnightblue',label='Loss');
plt.hist(binary_bdt.predict_proba(X_test[features][y_test==0])[:,1],bins=np.li
nspace(0,1,50),
         histtype='step',color='firebrick',label='No Loss');
# make the plot readable
plt.xlabel('Prediction from BDT',fontsize=12);
plt.ylabel('Events',fontsize=12);
plt.legend(frameon=False);
```





In [134]:
```
#Looking at the training set to make sure things still behave, we see they loo
k good
# However the smote events are the ones making up the clearly defined tail
# plot all predictions (both signal and background)
predictions = binary_bdt.predict_proba(X_train_smote[features])[:,1]
plt.figure();
plt.hist(predictions,bins=np.linspace(0,1,50),histtype='step',color='darkgree
n',label='All events');
# make the plot readable
plt.xlabel('Prediction from BDT',fontsize=12);
plt.ylabel('Events',fontsize=12);
plt.legend(frameon=False);

# plot signal and background separately
plt.figure();
plt.hist(binary_bdt.predict_proba(X_train_smote[features][y_train_smote==1])
[:,1],bins=np.linspace(0,1,50),
         histtype='step',color='midnightblue',label='Loss');
plt.hist(binary_bdt.predict_proba(X_train_smote[features][y_train_smote==0])
[:,1],bins=np.linspace(0,1,50),
         histtype='step',color='firebrick',label='No Loss');
# make the plot readable
plt.xlabel('Prediction from BDT',fontsize=12);
plt.ylabel('Events',fontsize=12);
plt.legend(frameon=False);
```


All events
Events
Prediction from BDT


Loss
No Loss
Events
Prediction from BDT