Xe1T_BandStuff (4)

August 30, 2017

1 ER/NR Band Discrimination

In [1]:
```
!rm -Rf ~/.cache ./pax_*

import logging
logging.getLogger('rootpy.stl').setLevel(logging.CRITICAL)
logging.getLogger('hax').setLevel(logging.CRITICAL)
logging.getLogger('requests').setLevel(logging.CRITICAL)
logging.getLogger('ROOT').setLevel(logging.CRITICAL)
logging.basicConfig(level=logging.CRITICAL)

import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
# Set name of notebook for folder to save plots in
notebook_name = 'Xe1T_BandStuff'

# run imports
%run "../helpers/initialize_midway.ipynb"

# get all plotfunctions
%run "../helpers/plot_functions.ipynb"
```

```
Initialization done, Notebook was last run on: 30/08/2017
```

In [3]:
```
hax.misc.code_hider()
```

Out[3]:
```
<IPython.core.display.HTML object>
```

In [4]:
```
# Initialize pax/hax

pax_version = '6.6.5'

# pax configuration
from pax import units, configuration, datastructure
pax_config = configuration.load_configuration('XENON1T')
tpc_radius = pax_config['DEFAULT']['tpc_radius']
```

```
tpc_height = pax_config['DEFAULT']['tpc_length']

# hax configuration
import hax
from lax.lichen import Lichen, RangeLichen, ManyLichen, StringLichen
from lax import __version__ as lax_version

hax.init(minitree_paths = ['/home/danielfm/',
                           '/scratch/midway2/berget2/minitrees/',
                           '/scratch/midway2/breur/miniforest/',
                           '/project/lgrandi/xenon1t/minitrees/pax_v' + pax_version+'/',
                             '/project2/lgrandi/xenon1t/minitrees/pax_v' + pax_version+'/'
         pax_version_policy = pax_version)
#make_minitrees = False
```

In [5]:
```
# Parse Datasets
dsets = hax.runs.datasets

# select the latest versions
dsets = dsets[(dsets.pax_version == '6.6.5')]

# Select tags
dsets = hax.runs.tags_selection(dsets, include=['sciencerun1'], exclude=['MVoff,blinded'
       'blinded,MVoff', 'blinded,earthquake', 'blinded,flash',
       'blinded,messy,PMTtrip,MVoff,flash', 'blinded,messy,flash', 'messy',
       'messy,flash', 'messy,flash,pmttrip', 'messy,pmttrip,flash',
       'messy,pmttrip,flash,ramping', 'noise', 'test', 'trip,messy'])

# Select with a processed location
dsets = dsets[(dsets.location != '')]
print('We start with %i processed SR1 datasets' % len(dsets))

dsets_list = []
sources = ['Rn220','AmBe','neutron_generator']
for i, source in enumerate(sources):
    dsets_list.append(dsets[(dsets.source__type == source) ])
    print('%s Datasets: %i' % (source, len(dsets_list[i])) )
```

```
We start with 3108 processed SR1 datasets
Rn220 Datasets: 238
AmBe Datasets: 332
neutron_generator Datasets: 47
```

In [6]:
```
import lax
lax_version = lax.__version__
from lax.lichens import sciencerun1
```

```
        list_of_treemakers = ['Corrections','Basics','Extended','Fundamentals', 'TotalProperties
        preselection_cuts = ['cs1 < 1000','cs2 < 300000','x**2 + y**2 < 45**2']

        dfs = []
        for i, source in enumerate(sources):
            #dfs.append(hax.minitrees.load(dsets_list[i].name,
            #                               treemakers=['Corrections','Basics','Extended','Fundam
            #                               preselection = 'cs1<500', num_workers=20))
            dfs.append(hax.minitrees.load(dsets_list[i].name, list_of_treemakers, preselection=p
```

```
cs1 < 1000 selection: 16649682 rows removed (5.92% passed)
cs2 < 300000 selection: 25671 rows removed (97.55% passed)
x**2 + y**2 < 45**2 selection: 354784 rows removed (65.26% passed)
cs1 < 1000 selection: 10379332 rows removed (6.08% passed)
cs2 < 300000 selection: 149598 rows removed (77.72% passed)
x**2 + y**2 < 45**2 selection: 178014 rows removed (65.89% passed)
cs1 < 1000 selection: 3750426 rows removed (5.55% passed)
cs2 < 300000 selection: 23166 rows removed (89.48% passed)
x**2 + y**2 < 45**2 selection: 47035 rows removed (76.13% passed)
```

```
In [7]: # get low energy er/nr cuts
        cut_list = [sciencerun1.LowEnergyRn220(), sciencerun1.LowEnergyAmBe(), sciencerun1.LowEn
```

```
In [8]: excluded_cuts = ['CutS1LowEnergyRange']
        for i in range(len(dfs)):
            print('%s Source Cut Summary:' % sources[i])
            dfs[i] = cut_list[i].process(dfs[i])
            for cut_name in cut_list[i].get_cut_names():
                if cut_name in excluded_cuts:
                    continue
                else:
                    dfs[i] = cuts.selection(dfs[i], dfs[i][cut_name], desc=cut_name)
            dfs[i] = cuts.below(dfs[i], 's1_range_50p_area', 400, desc='s1Width400')
            cuts.history(dfs[i])
            print('\n')
```

```
Rn220 Source Cut Summary:
CutFiducialCylinder1T selection: 582483 rows removed (12.59% passed)
CutS2Threshold selection: 24877 rows removed (70.36% passed)
CutS2AreaFractionTop selection: 1747 rows removed (97.04% passed)
CutS2SingleScatterSimple selection: 4912 rows removed (91.43% passed)
CutDAQVeto selection: 1903 rows removed (96.37% passed)
CutS1SingleScatter selection: 716 rows removed (98.58% passed)
CutS1AreaFractionTop selection: 692 rows removed (98.61% passed)
CutS2PatternLikelihood selection: 35418 rows removed (27.84% passed)
```

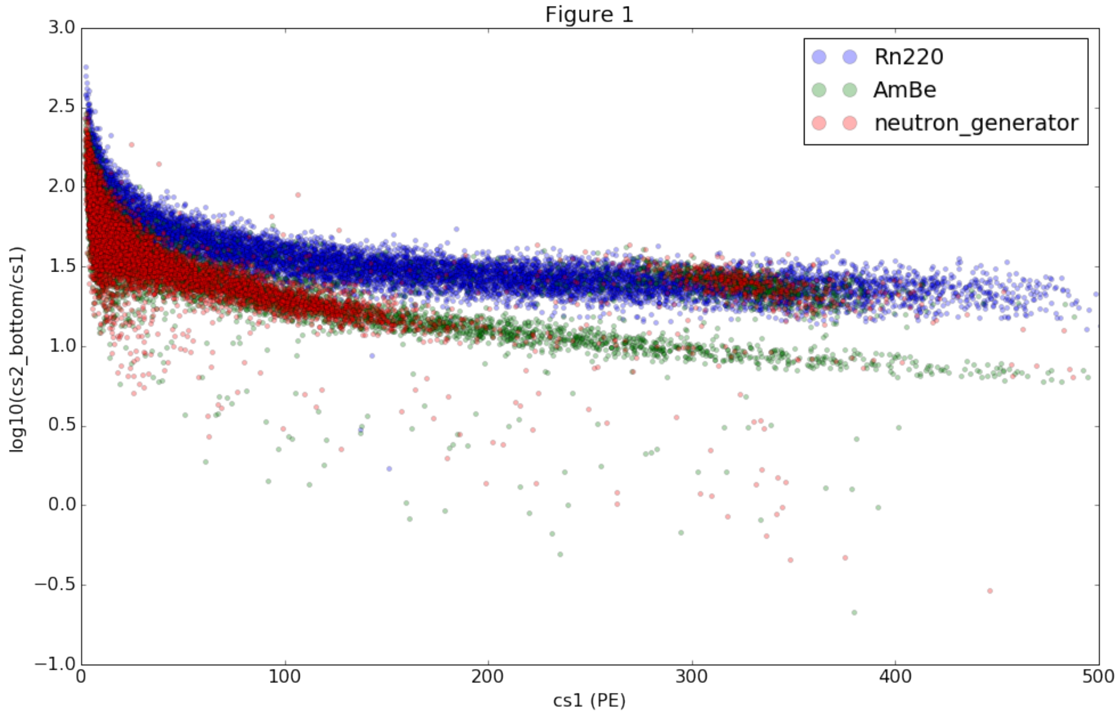
```
CutS2Tails selection: 753 rows removed (94.49% passed)
CutInteractionPeaksBiggest selection: 269 rows removed (97.92% passed)
CutS1PatternLikelihood selection: 2341 rows removed (81.48% passed)
CutS2Width selection: 243 rows removed (97.64% passed)
CutS1MaxPMT selection: 185 rows removed (98.16% passed)
s1Width400 selection: 11 rows removed (99.89% passed)


AmBe Source Cut Summary:
CutAmBeFiducial selection: 298695 rows removed (13.12% passed)
CutS2Threshold selection: 4682 rows removed (89.62% passed)
CutS2AreaFractionTop selection: 332 rows removed (99.18% passed)
CutS2SingleScatterSimple selection: 29230 rows removed (27.13% passed)
CutDAQVeto selection: 105 rows removed (99.03% passed)
CutS1SingleScatter selection: 93 rows removed (99.14% passed)
CutS1AreaFractionTop selection: 103 rows removed (99.04% passed)
CutS2PatternLikelihood selection: 1879 rows removed (82.24% passed)
CutS2Tails selection: 606 rows removed (93.03% passed)
CutInteractionPeaksBiggest selection: 47 rows removed (99.42% passed)
CutS1PatternLikelihood selection: 617 rows removed (92.33% passed)
CutS2Width selection: 549 rows removed (92.61% passed)
CutS1MaxPMT selection: 173 rows removed (97.49% passed)
s1Width400 selection: 12 rows removed (99.82% passed)


neutron_generator Source Cut Summary:
CutNGFiducial selection: 76837 rows removed (48.79% passed)
CutS2Threshold selection: 7254 rows removed (90.09% passed)
CutS2AreaFractionTop selection: 516 rows removed (99.22% passed)
CutS2SingleScatterSimple selection: 51318 rows removed (21.57% passed)
CutDAQVeto selection: 413 rows removed (97.07% passed)
CutS1SingleScatter selection: 269 rows removed (98.04% passed)
CutS1AreaFractionTop selection: 181 rows removed (98.65% passed)
CutS2PatternLikelihood selection: 3226 rows removed (75.66% passed)
CutS2Tails selection: 2049 rows removed (79.57% passed)
CutInteractionPeaksBiggest selection: 97 rows removed (98.78% passed)
CutS1PatternLikelihood selection: 521 rows removed (93.39% passed)
CutS2Width selection: 621 rows removed (91.56% passed)
CutS1MaxPMT selection: 192 rows removed (97.15% passed)
s1Width400 selection: 49 rows removed (99.25% passed)
```

In [9]:
```
#consts for CES
g2=11.463   # pe/e-
g1=0.1471 # pe/ph
w_value=0.0137
```

```
for i in range(len(dfs)):
    dfs[i]["CES"] = (dfs[i].cs2_bottom/g2 + dfs[i].cs1/g1)*w_value
    dfs[i]["DISC"] = np.log10(dfs[i].cs2_bottom/dfs[i].cs1)
```

1.0.1 Recoil Bands, ER Discrimination, and Leakage

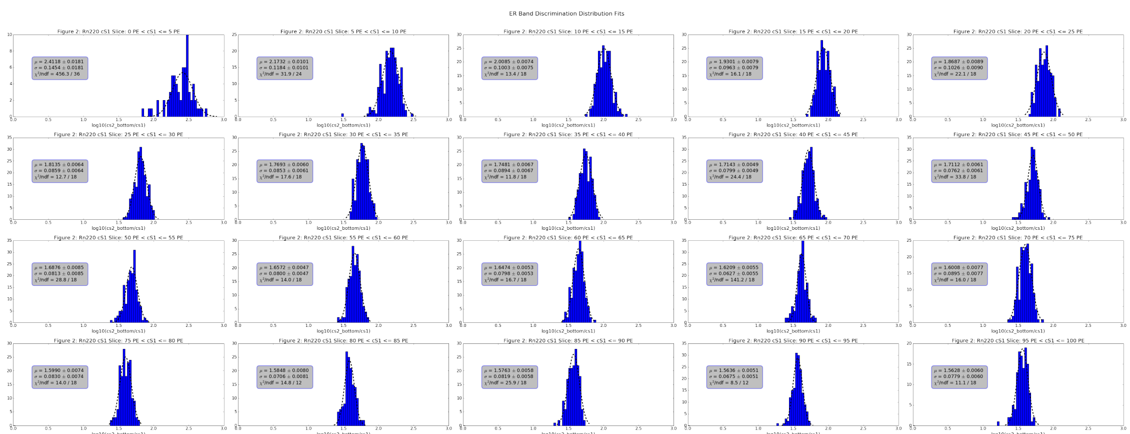
```
In [10]: fig = plt.figure(figsize = (16,10))

         for i in range(len(dfs)):
             plt.plot(dfs[i].cs1, np.log10(dfs[i].cs2_bottom/dfs[i].cs1),'o',label=sources[i],al

         plt.xlim(0,500)
         plt.xlabel('cs1 (PE)')
         plt.ylabel('log10(cs2_bottom/cs1)')
         plt.title('Recoil Bands, Low Energy Source Cuts')
         plt.legend(markerscale=3)

         plt.title('Figure 1')
         plt.show()
```




```
In [11]: # Develop ER Discrimination Line

         df_rn = dfs[0]
```

```
cs1_lim, cs1_width = 100, 5
cs1_bins = int(cs1_lim/cs1_width)
hist_range, hist_bins = [0,3], 100
hist_width = (hist_range[1]-hist_range[0])/hist_bins

fig = plt.figure(figsize = (12*5,6*4))
er_disc = []

for i in range(cs1_bins):

    # slice data in cs1
    cs1_min, cs1_max = i*cs1_width, (i+1)*cs1_width
    df = cuts.selection(df_rn, (df_rn['cs1'] > cs1_min) & (df_rn['cs1'] <= cs1_max), de


    # fill and fit discrimination hist

    x = df.DISC
    mean = np.mean(x)
    i_mean = int((mean/hist_width)+0.5)
    std = np.std(x)
    i_std = int((std/hist_width)+0.5)
    i_min, i_max = max(i_mean-3*i_std,0), min(i_mean+3*i_std,hist_bins)

    plt.subplot(4,5,i+1)
    ax = plt.gca()

    n, bins, patches = plt.hist(x, bins=hist_bins, range=hist_range)
    bin_centers = bins[:-1] + 0.5 * (bins[1:] - bins[:-1])
    x_fit = bin_centers[i_min:i_max]
    y_fit = n[i_min:i_max]
    guess = (mean, std, max(y_fit))
    popt, pcov = curve_fit(gaussian, x_fit, y_fit, p0=guess)
    fit = gaussian(x_fit, *popt)
    perr = np.sqrt(np.diag(pcov))
    chi2, ndf = chisquare_ndf(y_fit,fit)

    s = ('$\mu$ = %.4f $\pm$ %.4f  \n$\sigma$ = %.4f $\pm$ %.4f \n$\chi ^2$/ndf = %.1f
         % (popt[0], perr[0], popt[1], perr[1], chi2, ndf))
    bbox_props = dict(boxstyle="Round,pad=0.5", fc="gray", ec="blue", lw=2, alpha = 0.5
    plt.text(0.1, 0.5, s,  transform=ax.transAxes, bbox=bbox_props, size=18)
    x_plot = np.linspace(mean-3*std,mean+3*std,50)
    y_plot = gaussian(x_plot, *popt)
    plt.plot(x_plot, y_plot, c='k', linewidth=3, linestyle='dashed')
    plt.xlabel('log10(cs2_bottom/cs1)', fontsize=18)
    plt.title('Figure 2: Rn220 cS1 Slice: %i PE < cS1 <= %i PE' % (cs1_min,cs1_max), fo
```

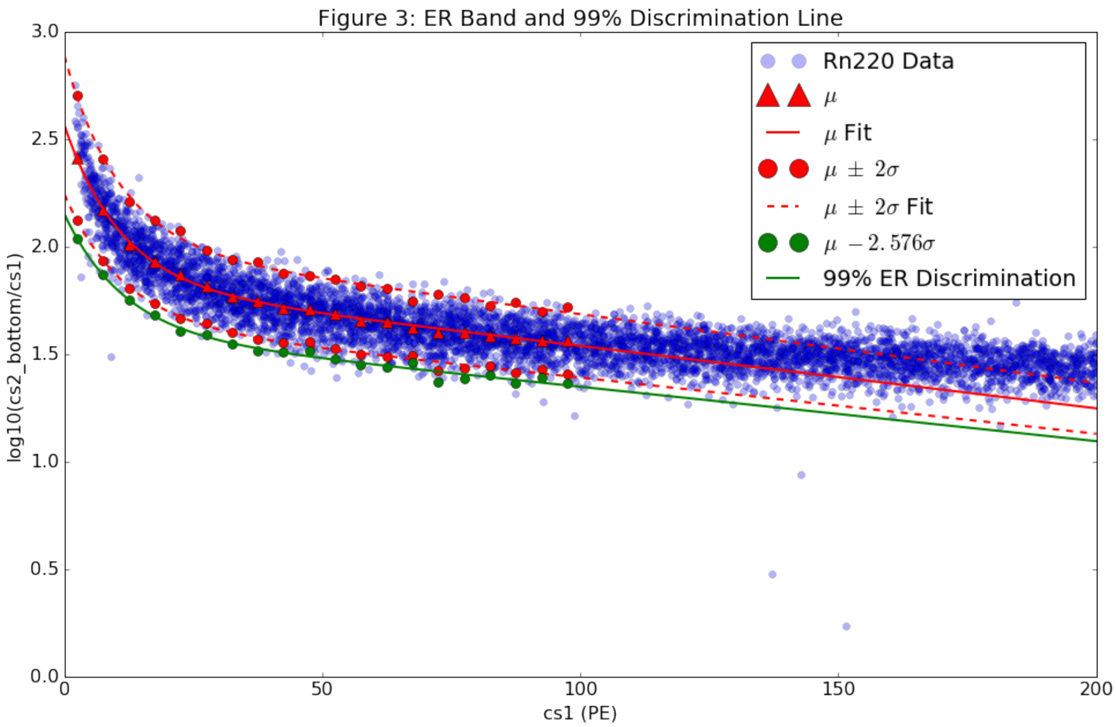
```
        er_disc.append([np.mean([cs1_min,cs1_max]),popt[0],popt[1]])

    er_disc = np.array(er_disc)

    plt.suptitle('ER Band Discrimination Distribution Fits', fontsize=22)
    plt.tight_layout(rect=[0, 0.03, 1, 0.95])


    plt.show()
```




```
In [12]: # Discrimination line
         def disc_exp(cs1, p0, p1, p2, p3):
             return np.exp(p0+p1*cs1) + p2 + p3*cs1

         # popt for SR0 99%
         sr0_99_popt = (-0.645351,-0.0544212,1.52071,-0.00108844)

         # Discrimination parameters for specific exclusion
         def disc_popt(er_disc, sigmas):
             x = er_disc[:,0]
             y = er_disc[:,1] + sigmas*er_disc[:,2]

             # guess from SR0 99%
             guess = sr0_99_popt

             popt, pcov = curve_fit(disc_exp, x, y, p0=guess)
             return popt
```

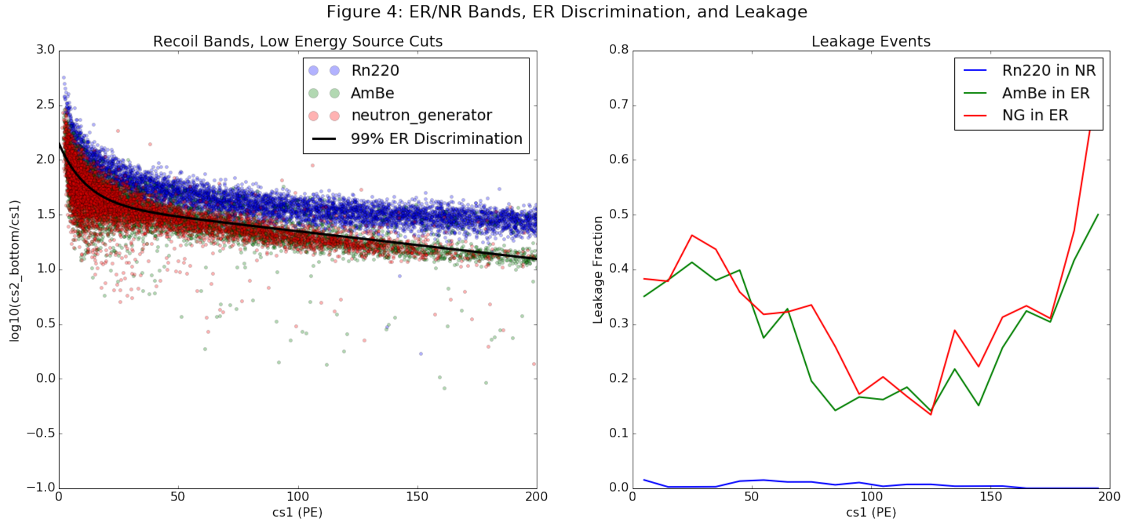
```
In [13]: fig = plt.figure(figsize = (16,10))


         plt.plot(df_rn.cs1, df_rn.DISC,'bo',label='Rn220 Data',alpha=0.3,markersize=6)
```

```
x = np.linspace(0,200,400)

plt.plot(er_disc[:,0], er_disc[:,1],'r^',label='$\mu$',markersize=10)
mean_popt = disc_popt(er_disc, 0)
mean_fit = disc_exp(x,*mean_popt)
plt.plot(x,mean_fit,'r-',lw=2,label='$\mu$ Fit')

plt.plot(er_disc[:,0], er_disc[:,1]+2*er_disc[:,2],'ro',label='$\mu\ \pm\ 2\sigma$',mar
p2s_popt = disc_popt(er_disc, 2)
p2s_fit = disc_exp(x,*p2s_popt)
plt.plot(x,p2s_fit,'r-',lw=2,linestyle='dashed',label='$\mu\ \pm\ 2\sigma$ Fit')

plt.plot(er_disc[:,0], er_disc[:,1]-2*er_disc[:,2],'ro',markersize=8)
n2s_popt = disc_popt(er_disc, -2)
n2s_fit = disc_exp(x,*n2s_popt)
plt.plot(x,n2s_fit,'r-',lw=2,linestyle='dashed')

plt.plot(er_disc[:,0], er_disc[:,1]-2.576*er_disc[:,2],'go',markersize=8,label='$\mu\ -
disc_99_popt = disc_popt(er_disc, -2.576)
disc_99_fit = disc_exp(x,*disc_99_popt)
plt.plot(x,disc_99_fit,'g-',lw=2,label='99% ER Discrimination')

plt.xlim(0,200)
plt.xlabel('cs1 (PE)')
plt.ylabel('log10(cs2_bottom/cs1)')
plt.title('Figure 3: ER Band and 99% Discrimination Line')
plt.legend(markerscale=2)

plt.show()
```




```
In [14]: fig = plt.figure(figsize = (24,10))
         plt.suptitle('Figure 4: ER/NR Bands, ER Discrimination, and Leakage', fontsize=22)

         plt.subplot(121)
         for i in range(len(dfs)):
             plt.plot(dfs[i].cs1, np.log10(dfs[i].cs2_bottom/dfs[i].cs1),'o',label=sources[i],al

         plt.plot(x,disc_99_fit,'k-',lw=3,label='99% ER Discrimination')

         plt.xlim(0,200)
         plt.xlabel('cs1 (PE)')
         plt.ylabel('log10(cs2_bottom/cs1)')
         plt.title('Recoil Bands, Low Energy Source Cuts')
         plt.legend(markerscale=3)

         plt.subplot(122)

         # Calculate leakage ratios
         cs1_lim, cs1_width = 200, 10
         cs1_bins = int(cs1_lim/cs1_width)
         leakage_ratios = []
         for i in range(cs1_bins):

             # slice data in cs1
```

```
    cs1_min, cs1_max = i*cs1_width, (i+1)*cs1_width
    ratios = []
    for i in range(len(sources)):
        df_slice = cuts.selection(dfs[i], (dfs[i]['cs1'] > cs1_min) & (dfs[i]['cs1'] <=
        if i==0:
            df_slice_disc = cuts.selection(df_slice,df_slice['DISC'] < disc_exp(df_slic
        else:
            df_slice_disc = cuts.selection(df_slice,df_slice['DISC'] > disc_exp(df_slic
        ratios.append(len(df_slice_disc)/len(df_slice))
    leakage_ratios.append([np.mean([cs1_min,cs1_max]),ratios[0],ratios[1],ratios[2]])
leakage_ratios = np.array(leakage_ratios)

plt.plot(leakage_ratios[:,0],leakage_ratios[:,1],'-',lw=2,label='Rn220 in NR')
plt.plot(leakage_ratios[:,0],leakage_ratios[:,2],'-',lw=2,label='AmBe in ER')
plt.plot(leakage_ratios[:,0],leakage_ratios[:,3],'-',lw=2,label='NG in ER')

plt.xlabel('cs1 (PE)')
plt.ylabel('Leakage Fraction')
plt.legend(markerscale=3)
plt.title('Leakage Events')

plt.show()
```



1.0.2 How Else Can We Discriminate ER/NR? ML!

```
In [15]: # ML imports
         from matplotlib.colors import ListedColormap
         from pandas.tools.plotting import scatter_matrix
         from sklearn import model_selection
         from sklearn.metrics import classification_report
```

```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
```

In [16]:
```
# prepare data
dfs_lowE = []
for i in range(len(dfs)):
    dfs_lowE.append(cuts.below(dfs[i],'cs1',200,quiet=True))
    if sources[i] == 'Rn220':
        dfs_lowE[i]['recoil'] = 'er'
    else:
        dfs_lowE[i]['recoil'] = 'nr'

df_ml = pd.concat(dfs_lowE)
df_ml_min = df_ml[['cs1','DISC','recoil']]

# Count recoil events
er_tot = len(df_ml_min[df_ml_min.recoil=='er'])
print('%i total ER events (Rn220)' % er_tot)
nr_tot = len(df_ml_min[df_ml_min.recoil=='nr'])
print('%i total NR events (AmBe and NG)' % nr_tot)
```

```
6030 total ER events (Rn220)
11243 total NR events (AmBe and NG)
```

In [17]:
```
# Split-out validation dataset
array = df_ml_min.values
X = array[:,0:len(df_ml_min.keys())-1]
Y = array[:,len(df_ml_min.keys())-1]
validation_size = 0.20
seed = 7
X_train, X_validation, Y_train, Y_validation = model_selection.train_test_split(X, Y, t
```

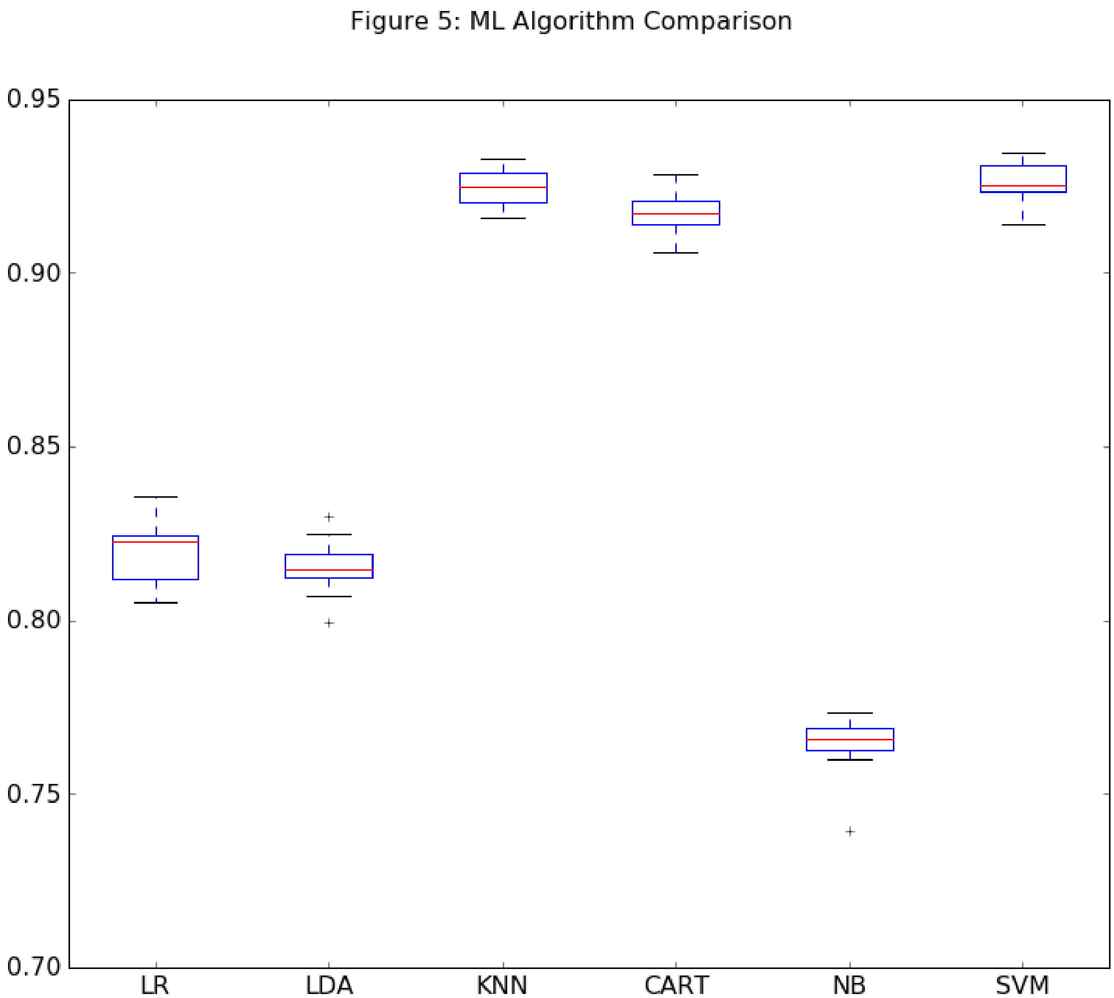
In [18]:
```
# Spot Check Algorithms
scoring = 'accuracy'

models = []
models.append(('LR', LogisticRegression()))
models.append(('LDA', LinearDiscriminantAnalysis()))
models.append(('KNN', KNeighborsClassifier()))
models.append(('CART', DecisionTreeClassifier()))
models.append(('NB', GaussianNB()))
models.append(('SVM', SVC()))
```

```
# evaluate each model in turn
print('ML Algorithm Accuracy Summary; Mean (Std) \n')
results = []
names = []
for name, model in models:
    kfold = model_selection.KFold(n_splits=10, random_state=seed)
    cv_results = model_selection.cross_val_score(model, X_train, Y_train, cv=kfold, sco
    results.append(cv_results)
    names.append(name)
    msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.std())
    print(msg)
```

```
ML Algorithm Accuracy Summary; Mean (Std)

LR: 0.819655 (0.008570)
LDA: 0.815312 (0.008217)
KNN: 0.924809 (0.005524)
CART: 0.916848 (0.006392)
NB: 0.763785 (0.009051)
SVM: 0.925749 (0.006283)
```

1.0.3 Running the ML algorith accuracy code cell provides a list of each algorithm short name, the mean accuracy and the standard deviation accuracy.

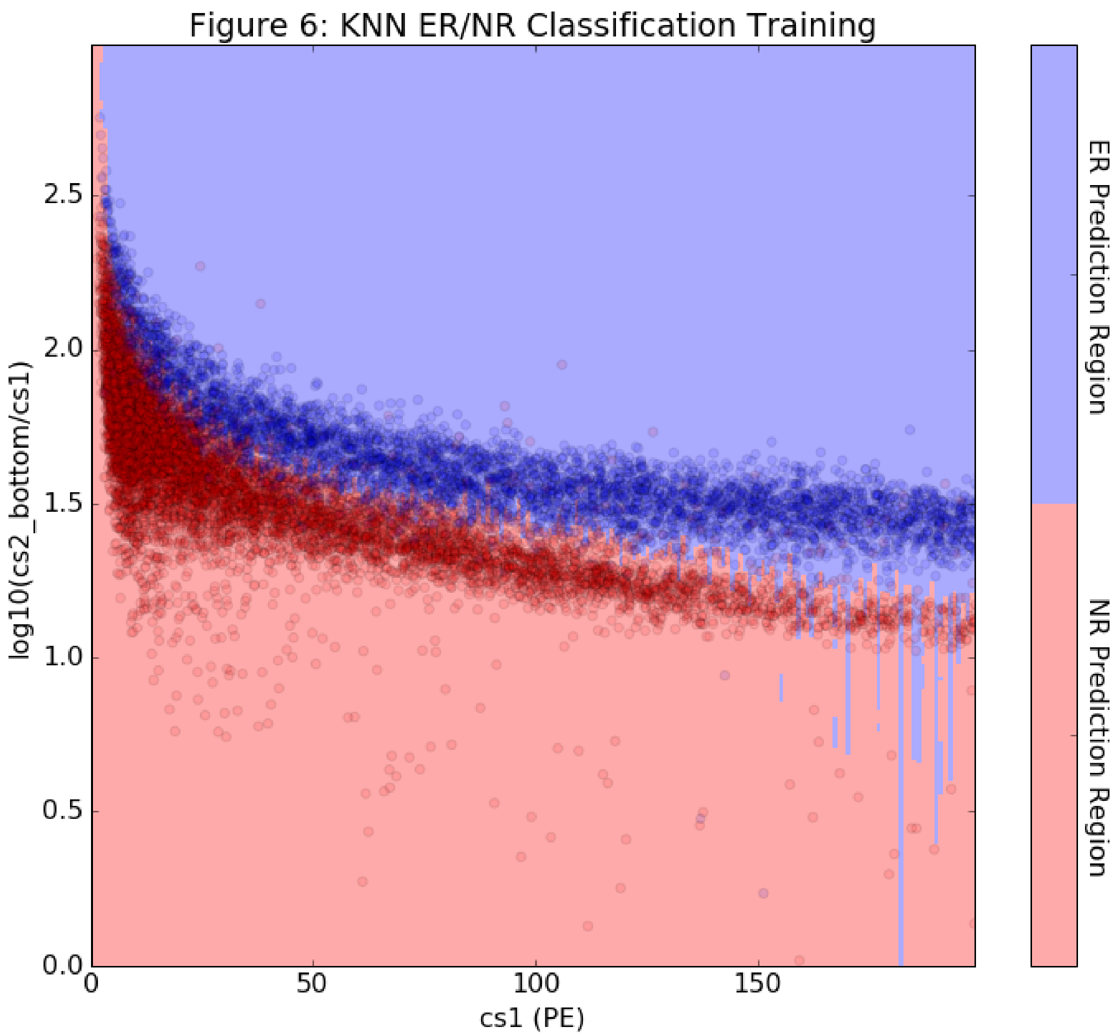
```
In [19]: # Compare Algorithms
         fig = plt.figure()
         fig.suptitle('Figure 5: ML Algorithm Comparison')
         ax = fig.add_subplot(111)
         plt.boxplot(results)
         ax.set_xticklabels(names)
         plt.show()
```



1.0.4 The ML algorithm comparison chart also provides a box and whisker plot showing the spread of the accuracy scores across each cross validation fold for each algorithm. From these results, it would suggest that both KNN and SVM are perhaps worthy of further study on this problem.

In [20]:
```
n_neighbors=15

cmap_light = ListedColormap(['#AAAAFF', '#FFAAAA'])
cmap_bold = ListedColormap(['#0000FF', '#FF0000'])

knn = KNeighborsClassifier(n_neighbors, weights='distance')
knn.fit(X_train,Y_train)

# Plot the decision boundary. For that, we will assign a color to each
# point in the mesh [x_min, x_max]x[y_min, y_max].
x_min, x_max = X_train[:, 0].min(), X_train[:, 0].max()
```

```python
y_min, y_max = X_train[:, 1].min(), X_train[:, 1].max()
xx, yy = np.meshgrid(np.arange(0, 200, 1),
                     np.arange(0, 3, 0.01))
Z = knn.predict(np.c_[xx.ravel(), yy.ravel()])
lookupTable, Z = np.unique(np.array(Z),return_inverse=True)
Z = Z.reshape(xx.shape)

fig, ax = plt.subplots()
plt.pcolormesh(xx, yy, Z, cmap=cmap_light)
cbar = plt.colorbar()
cbar.set_ticks([0.25,0.75])
cbar.set_ticklabels(['ER Prediction Region','NR Prediction Region'])
cbar.ax.set_yticklabels(cbar.ax.get_yticklabels(),rotation=-90)
cbar.ax.invert_yaxis()

# Plot also the training points
lookupTable, Y_colors = np.unique(np.array(Y_train),return_inverse=True)
ax.scatter(X_train[:, 0], X_train[:, 1], color=Y_colors, cmap=cmap_bold,
            edgecolor='k', s=30, alpha=0.1)
plt.xlim(xx.min(), xx.max())
plt.ylim(yy.min(), yy.max())
plt.title("Figure 6: KNN ER/NR Classification Training")
plt.xlabel('cs1 (PE)')
plt.ylabel('log10(cs2_bottom/cs1)')

plt.show()
```

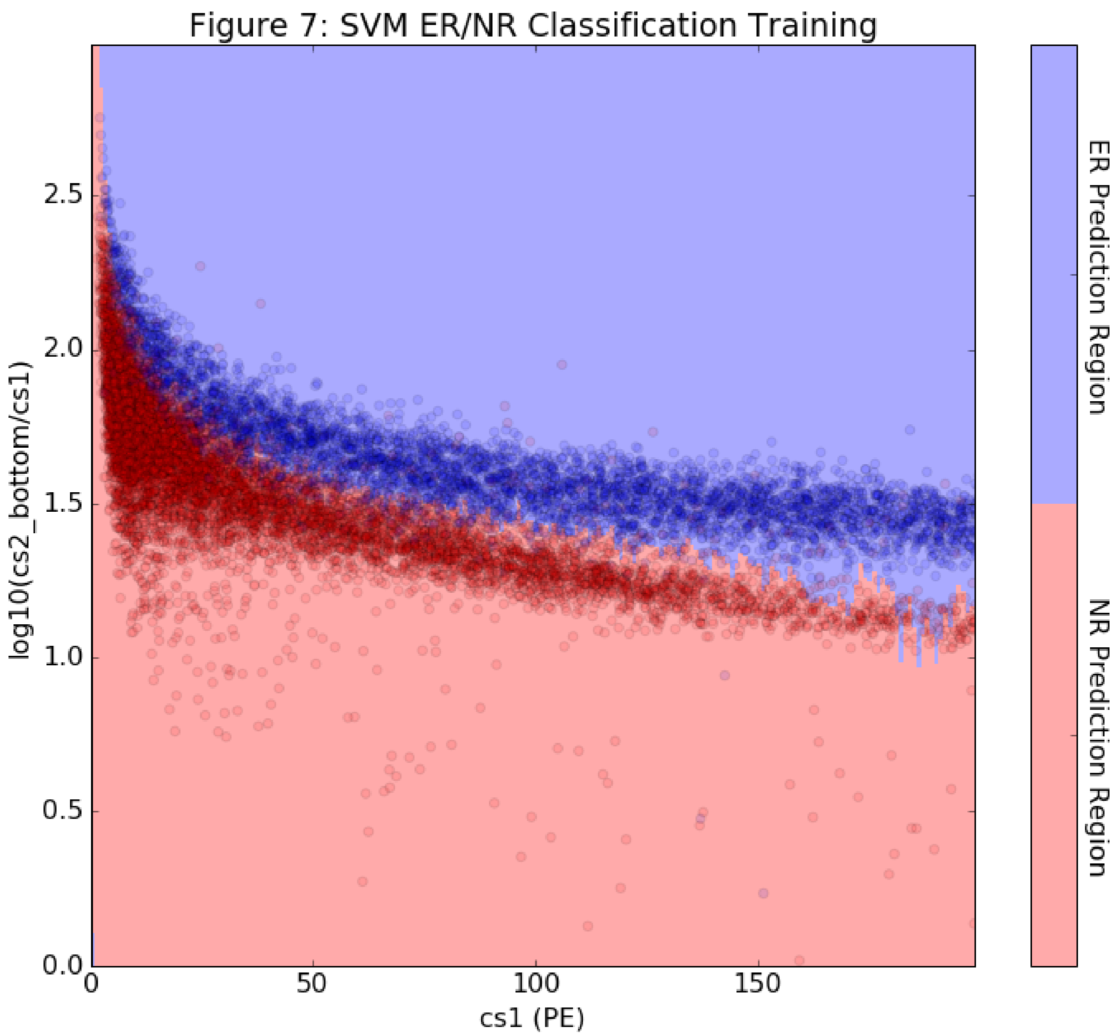



```
In [21]: print( list( df.keys() ) )
```

```
['run_number', 'event_number', 's2_area_tailcut_set_by', 's2_over_tdiff', 'tailcut_set_by', 'nea
```

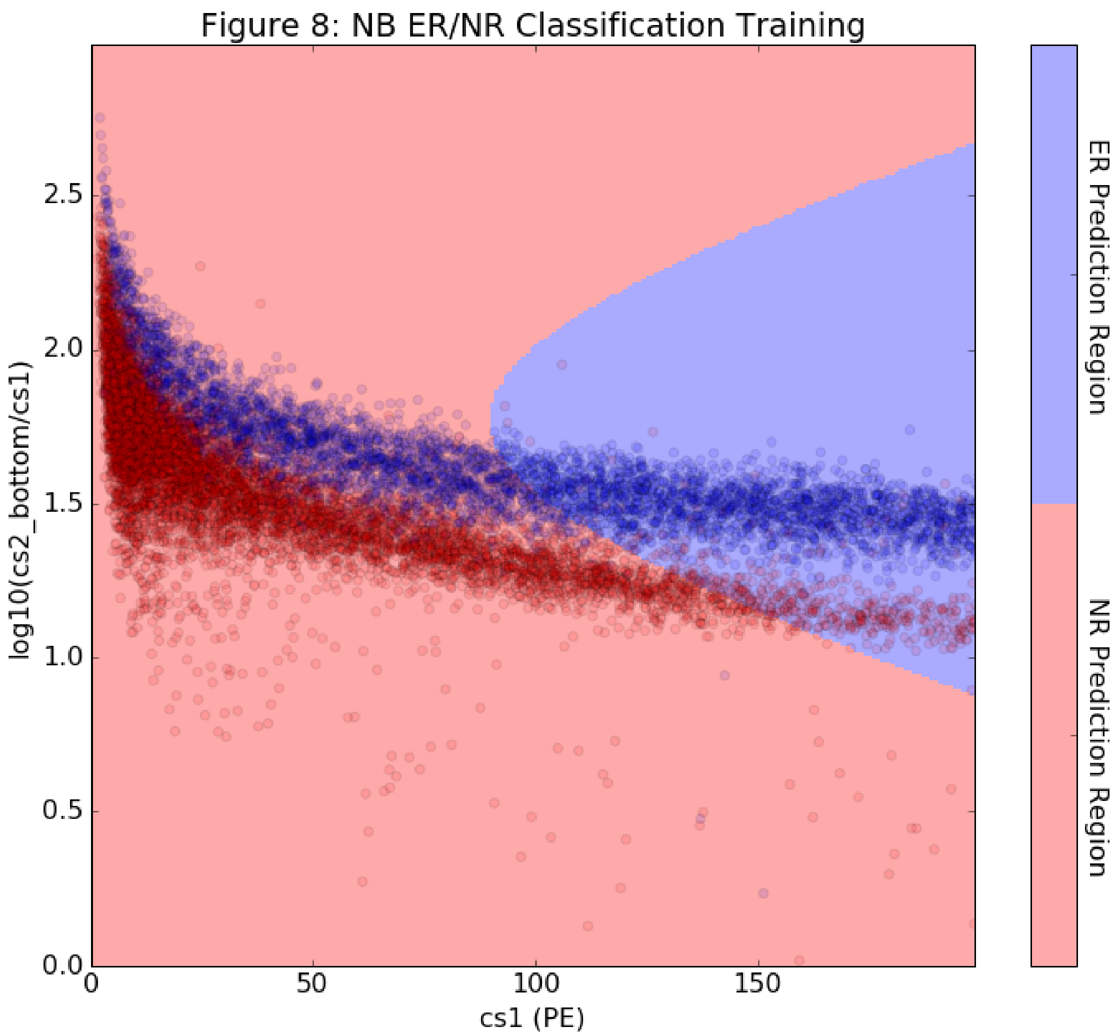
```
In [22]: from sklearn import svm

         cmap_light = ListedColormap(['#AAAAFF', '#FFAAAA'])
         cmap_bold = ListedColormap(['#0000FF', '#FF0000'])

         svm_clf= svm.SVC()

         SVC(C=1.0, cache_size=200, class_weight=None, coef0=0.0,
             decision_function_shape='ovo', degree=3, gamma='auto', kernel='rbf',
             max_iter=-1, probability=False, random_state=None, shrinking=True,
             tol=0.001, verbose=False)
```

```python
svm_clf.fit(X_train,Y_train)


# Plot the decision boundary. For that, we will assign a color to each
# point in the mesh [x_min, x_max]x[y_min, y_max].
x_min, x_max = X_train[:, 0].min(), X_train[:, 0].max()
y_min, y_max = X_train[:, 1].min(), X_train[:, 1].max()
xx, yy = np.meshgrid(np.arange(0, 200, 1),
                     np.arange(0, 3, 0.01))
Z = svm_clf.predict(np.c_[xx.ravel(), yy.ravel()])
lookupTable, Z = np.unique(np.array(Z),return_inverse=True)
Z = Z.reshape(xx.shape)

fig, ax = plt.subplots()
plt.pcolormesh(xx, yy, Z, cmap=cmap_light)
cbar = plt.colorbar()
cbar.set_ticks([0.25,0.75])
cbar.set_ticklabels(['ER Prediction Region','NR Prediction Region'])
cbar.ax.set_yticklabels(cbar.ax.get_yticklabels(),rotation=-90)
cbar.ax.invert_yaxis()

# Plot also the training points
lookupTable, Y_colors = np.unique(np.array(Y_train),return_inverse=True)
ax.scatter(X_train[:, 0], X_train[:, 1], color=Y_colors, cmap=cmap_bold,
            edgecolor='k', s=30, alpha=0.1)
plt.xlim(xx.min(), xx.max())
plt.ylim(yy.min(), yy.max())
plt.title("Figure 7: SVM ER/NR Classification Training")
plt.xlabel('cs1 (PE)')
plt.ylabel('log10(cs2_bottom/cs1)')

plt.show()
```



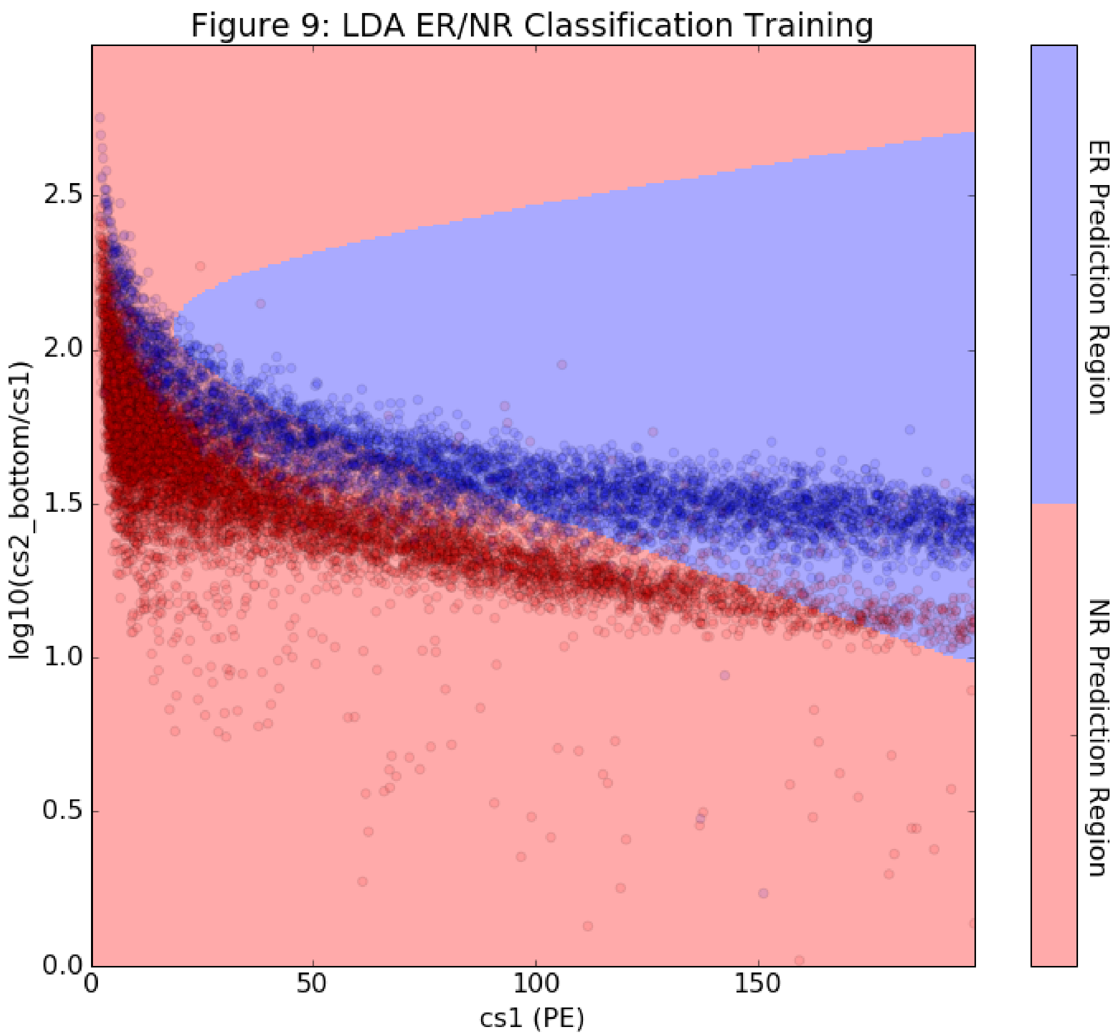
In [23]:
```
from sklearn.naive_bayes import GaussianNB

nb_clf = GaussianNB()

nb_clf.fit(X_train,Y_train)
GaussianNB(priors=None)

# Plot the decision boundary. For that, we will assign a color to each
# point in the mesh [x_min, x_max]x[y_min, y_max].
x_min, x_max = X_train[:, 0].min(), X_train[:, 0].max()
y_min, y_max = X_train[:, 1].min(), X_train[:, 1].max()
xx, yy = np.meshgrid(np.arange(0, 200, 1),
                     np.arange(0, 3, 0.01))
Z = nb_clf.predict(np.c_[xx.ravel(), yy.ravel()])
lookupTable, Z = np.unique(np.array(Z),return_inverse=True)
```

```python
Z = Z.reshape(xx.shape)

fig, ax = plt.subplots()
plt.pcolormesh(xx, yy, Z, cmap=cmap_light)
cbar = plt.colorbar()
cbar.set_ticks([0.25,0.75])
cbar.set_ticklabels(['ER Prediction Region','NR Prediction Region'])
cbar.ax.set_yticklabels(cbar.ax.get_yticklabels(),rotation=-90)
cbar.ax.invert_yaxis()

# Plot also the training points
lookupTable, Y_colors = np.unique(np.array(Y_train),return_inverse=True)
ax.scatter(X_train[:, 0], X_train[:, 1], color=Y_colors, cmap=cmap_bold,
            edgecolor='k', s=30, alpha=0.1)
plt.xlim(xx.min(), xx.max())
plt.ylim(yy.min(), yy.max())
plt.title("Figure 8: NB ER/NR Classification Training")
plt.xlabel('cs1 (PE)')
plt.ylabel('log10(cs2_bottom/cs1)')

plt.show()
```




```
In [24]: from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
         import numpy as np

         lda_clf = QuadraticDiscriminantAnalysis()
         lda_clf.fit(X_train,Y_train)

         LinearDiscriminantAnalysis(n_components=None, priors=None, shrinkage=None,
                       solver='svd', store_covariance=False, tol=0.0001)



         # Plot the decision boundary. For that, we will assign a color to each
         # point in the mesh [x_min, x_max]x[y_min, y_max].
         x_min, x_max = X_train[:, 0].min(), X_train[:, 0].max()
         y_min, y_max = X_train[:, 1].min(), X_train[:, 1].max()
```

```
xx, yy = np.meshgrid(np.arange(0, 200, 1),
                     np.arange(0, 3, 0.01))
Z = lda_clf.predict(np.c_[xx.ravel(), yy.ravel()])
lookupTable, Z = np.unique(np.array(Z),return_inverse=True)
Z = Z.reshape(xx.shape)

fig, ax = plt.subplots()
plt.pcolormesh(xx, yy, Z, cmap=cmap_light)
cbar = plt.colorbar()
cbar.set_ticks([0.25,0.75])
cbar.set_ticklabels(['ER Prediction Region','NR Prediction Region'])
cbar.ax.set_yticklabels(cbar.ax.get_yticklabels(),rotation=-90)
cbar.ax.invert_yaxis()

# Plot also the training points
lookupTable, Y_colors = np.unique(np.array(Y_train),return_inverse=True)
ax.scatter(X_train[:, 0], X_train[:, 1], color=Y_colors, cmap=cmap_bold,
            edgecolor='k', s=30, alpha=0.1)
plt.xlim(xx.min(), xx.max())
plt.ylim(yy.min(), yy.max())
plt.title("Figure 9: LDA ER/NR Classification Training")
plt.xlabel('cs1 (PE)')
plt.ylabel('log10(cs2_bottom/cs1)')

plt.show()
```



1.0.5 Even though the ML comparison plot looks correct and even though the KNN/SVM/LDA/NB ER/NR Classification Training plots also look correct, I cannot help but wonder if we did make use of the pulse shape information. After doing some investigative work and asking Darryl a couple of questions--I was able to do some minor modifications to Ted's program. It is obvious from the classification training plots that LDA and NB are horrible algorithms to use for the ER and NR discrimination assignment.

1.0.6 In the case of svm.SVR, the default is rbf, which is a type of kernel. We have a few other choices though. If we check the documentation, we find we have the kernels: 'linear', 'poly', 'rbf', 'sigmoid', 'precomputed' or a callable. Now, we try the various kernels and see which kernel performed the best.

```
In [34]: from sklearn.svm import SVR
         import numpy as np
```

```
# Split-out validation dataset
array = df_ml_min.values
X = array[:,0:len(df_ml_min.keys())-1]
Y = array[:,len(df_ml_min.keys())-1]
validation_size = 0.20
seed = 7
X_train, X_validation, Y_train, Y_validation = model_selection.train_test_split(X, Y, t

for k in ['linear','poly','rbf','sigmoid']:
    clf = svm.SVR(kernel=k)
    clf.fit(X_train,Y_train)
    confidence = clf.score(X_test, Y_test)
    print(k,confidence)
```

```
---------------------------------------------------------------------------

ValueError                                Traceback (most recent call last)

<ipython-input-34-dc59c8940dce> in <module>()
     12 for k in ['linear','poly','rbf','sigmoid']:
     13     clf = svm.SVR(kernel=k)
---> 14     clf.fit(X_train,Y_train)
     15     confidence = clf.score(X_test, Y_test)
     16     print(k,confidence)


/project/lgrandi/anaconda3/envs/pax_head/lib/python3.4/site-packages/sklearn/svm/base.py
    150
    151         X, y = check_X_y(X, y, dtype=np.float64, order='C', accept_sparse='csr')
--> 152         y = self._validate_targets(y)
    153
    154         sample_weight = np.asarray([]


/project/lgrandi/anaconda3/envs/pax_head/lib/python3.4/site-packages/sklearn/svm/base.py
    210         # Regression models should not have a class_weight_ attribute.
    211         self.class_weight_ = np.empty(0)
--> 212         return column_or_1d(y, warn=True).astype(np.float64)
    213
    214     def _warn_from_fit_status(self):


ValueError: could not convert string to float: 'nr'
```

In [33]:
```
# Fit regression model
from sklearn.svm import SVR
```

```python
svr_rbf = SVR(kernel='rbf', C=1e4, gamma=0.1)
svr_lin = SVR(kernel='linear', C=1e4)
#svr_poly = SVR(kernel='poly', C=1e4, degree=2)
#y_rbf = svr_rbf.fit(X_train,Y_train).predict(X)
#y_lin = svr_lin.fit(X_train,Y_train).predict(X)
#y_poly = svr_poly.fit(X_train,Y_train).predict(X)
```

In [ ]:

In [ ]: