In [1]:

```
import numpy as np
import pandas as pd
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import log_loss,accuracy_score,confusion_matri

from matplotlib import pyplot as plt
import seaborn as sns
```

load data

In [2]:

```
x_train = np.loadtxt('./data_digits_8_vs_9_noisy/x_train.csv', delin
x_test = np.loadtxt('./data_digits_8_vs_9_noisy/x_test.csv', delimit
y_train = np.loadtxt('./data_digits_8_vs_9_noisy/y_train.csv', delin
y_test = np.loadtxt('./data_digits_8_vs_9_noisy/y_test.csv', delimit
```

In [3]:

```
def calc_confusion_matrix_for_threshold(ytrue_N, yproba1_N, thresh)
    ''' Compute the confusion matrix for a given probabilistic class

    Args
    ----
    ytrue_N : 1D array of floats
        Each entry represents the binary value (0 or 1) of 'true' la
        One entry per example in current dataset
    yproba1_N : 1D array of floats
        Each entry represents a probability (between 0 and 1) that c
        One entry per example in current dataset
        Needs to be same size as ytrue_N
    thresh : float
        Scalar threshold for converting probabilities into hard deci
        Calls an example "positive" if yproba1 >= thresh

    Returns
    -------
    cm_df : Pandas DataFrame
        Can be printed like print(cm_df) to easily display results
    '''
    cm = confusion_matrix(ytrue_N, yproba1_N >= thresh)
    cm_df = pd.DataFrame(data=cm, columns=[0, 1], index=[0, 1])
    cm_df.columns.name = 'Predicted'
    cm_df.index.name = 'True'
    return cm_df
```

explore what happens when we limit the iterations allowed for the solver to converge on its solution.

For the values i = 1; 2; : : : ; 40, build a logistic regression model with the max_iter set to i.

In [4]:

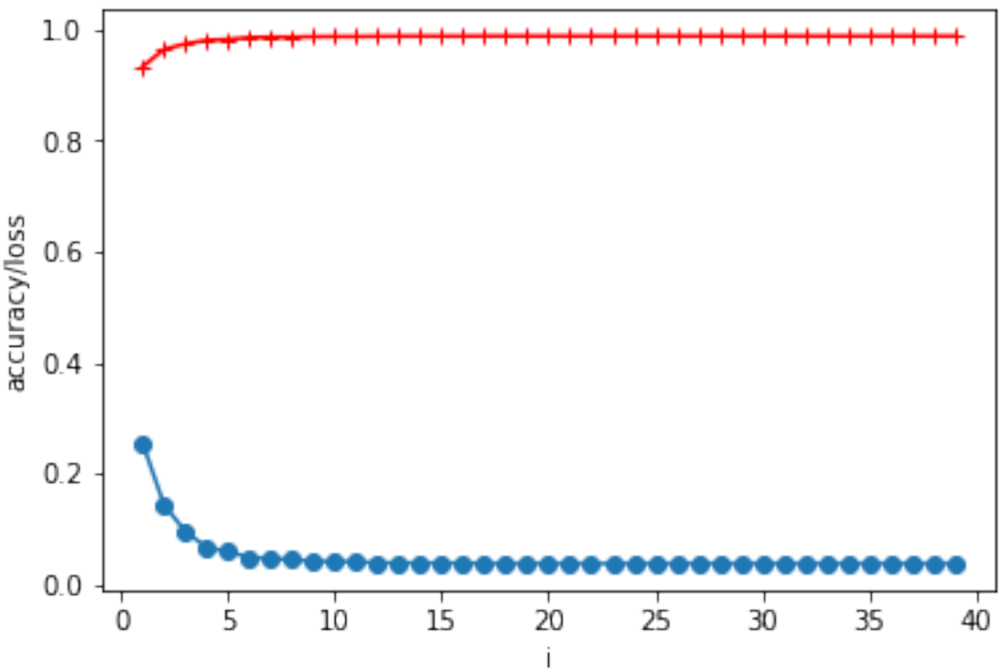
```
tr_loss_list = list()
tr_score_list = list()
weight_list = list()


# Build and evaluate model for each value i
for i in list(range(1,40)):

    logreg = LogisticRegression(penalty='l1', max_iter = i , solver=
    logreg.fit(x_train,y_train) # fit model

    w0 = logreg.coef_[0][0]
    weight_list.append(w0)

    y_pred_proba = logreg.predict_proba(x_train)[:,1] # convention
    loss = log_loss(y_train, y_pred_proba)
    tr_loss_list.append(loss)

    predict = logreg.predict(x_train)
    score = accuracy_score(y_train, predict)
    tr_score_list.append(score)
```

In [5]:

```
i = list(range(1,40))
plt.xlabel('i');
plt.ylabel('accuracy/loss');
plt.plot(i,tr_loss_list,marker='o')
plt.plot(i,tr_score_list,c="red",marker='+')
```

Out[5]:

```
[<matplotlib.lines.Line2D at 0x1a20f54cc0>]
```



From our plot, we could know that, with increasing i, the maximum number of iterations taken for the solvers to converge, the accuracy increases and the loss decreases. Higher i leads to better convergence, but it also becomes more "expensive" computationally. It indicates that there is a trade-off between cost/accuracy and iteration time.

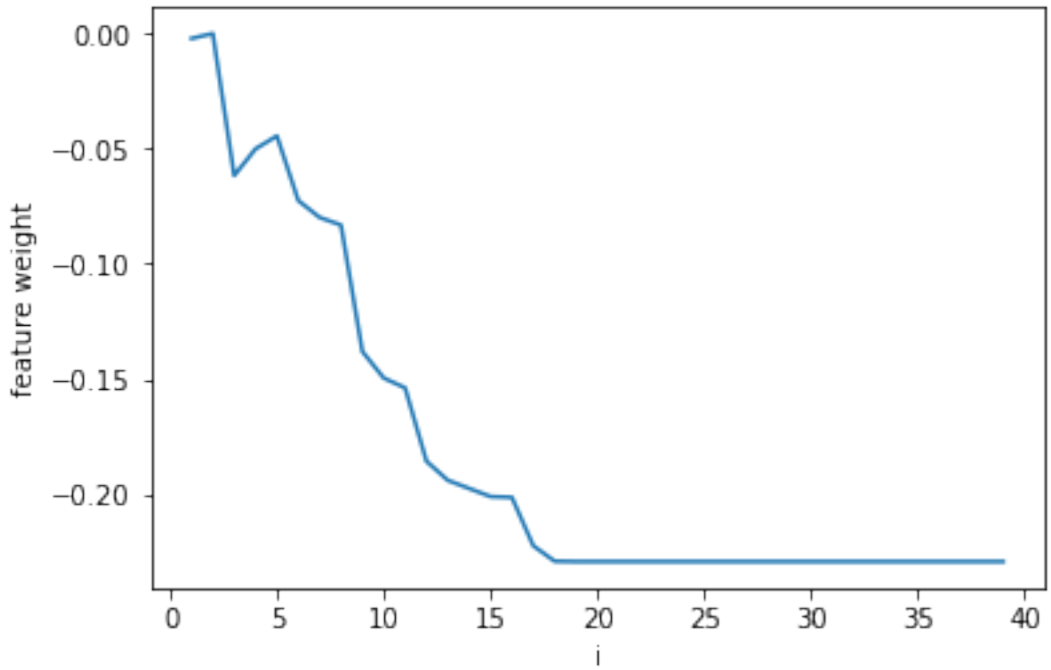
plot with the values of i as x-axis and with the feature weight as y

In [6]:

```
plt.xlabel('i');
plt.ylabel('feature weight');
plt.plot(i,weight_list)
```

Out[6]:

```
[<matplotlib.lines.Line2D at 0x1a21d3c4a8>]
```



explore different values of the inverse penalty strength C

In [7]:

```
tr_loss_list2 = list()
tr_score_list2 = list()

C_grid = np.logspace(-9, 6, 31)

# Build and evaluate model for each value C
for C in C_grid:

    logreg = LogisticRegression(penalty='l1', C=C , solver='liblinea
    print(logreg)
    logreg.fit(x_train,np.ravel(y_train)) # fit model
```

```
    y_pred_proba = logreg.predict_proba(x_test)[:,1] # convention
    loss = log_loss(y_test, y_pred_proba)
    tr_loss_list2.append(loss)


    predict = logreg.predict(x_test)
    score = accuracy_score(y_test, predict)
    tr_score_list2.append(score)

best_i = np.argmin(tr_loss_list2)
best_c = C_grid[best_i]
bestmodel_c = LogisticRegression(penalty='l1', C=best_c, solver='lil
```

```
LogisticRegression(C=1e-09, class_weight=None, dual=Fa
lse, fit_intercept=True,
          intercept_scaling=1, max_iter=10000, multi_c
lass='ovr', n_jobs=1,
          penalty='l1', random_state=0, solver='liblin
ear', tol=0.0001,
          verbose=0, warm_start=False)
LogisticRegression(C=3.1622776601683795e-09, class_wei
ght=None, dual=False,
          fit_intercept=True, intercept_scaling=1, max
_iter=10000,
          multi_class='ovr', n_jobs=1, penalty='l1', r
andom_state=0,
          solver='liblinear', tol=0.0001, verbose=0, w
arm_start=False)
LogisticRegression(C=1e-08, class_weight=None, dual=Fa
lse, fit_intercept=True,
          intercept_scaling=1, max_iter=10000, multi_c
lass='ovr', n_jobs=1,
```

In [8]:

```
bestmodel_c.fit(x_train, np.ravel(y_train))
print(calc_confusion_matrix_for_threshold(y_test, bestmodel_c.predic
print("Best C-value for lr data: %.3f" % best_c)

min_logloss = tr_loss_list2[best_i]
print("Test set log-loss at best C-value: %.4f" % min_logloss)

score = tr_score_list2[best_i]
print("Test set accuracy score at best C-value: %.4f" % score)
```

```
Predicted    0    1
True
0          943   31
1           38  971
Best C-value for lr data: 0.316
Test set log-loss at best C-value: 0.0910
Test set accuracy score at best C-value: 0.9652
```

In [9]:

```
bestmodel_c = LogisticRegression(penalty='l1', C=best_c, solver='lil
bestmodel_c.fit(x_train, np.ravel(y_train))
predict = bestmodel_c.predict(x_test)
```

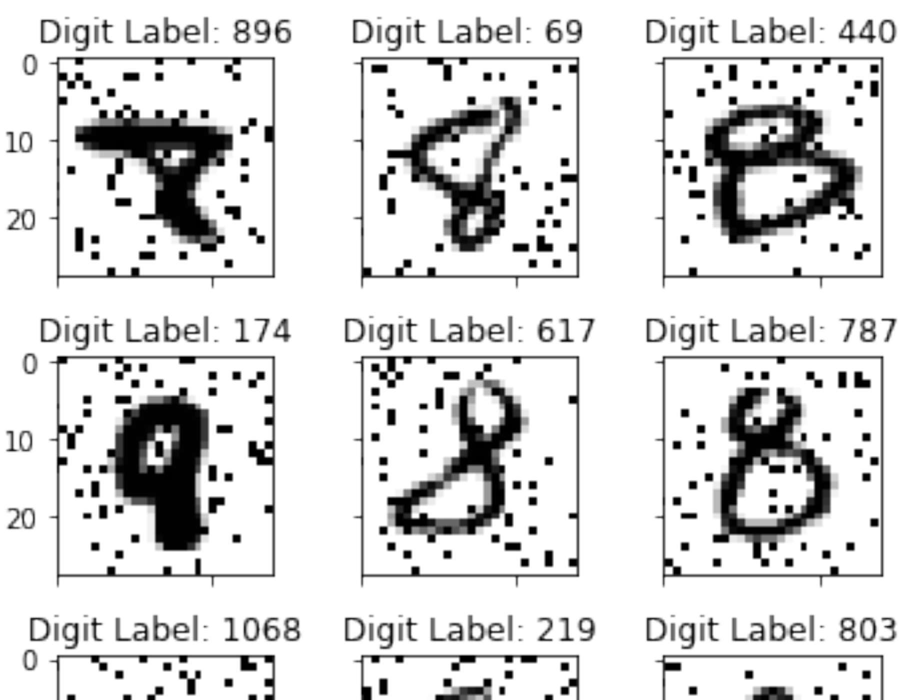
Analyze some of the mistakes that your best model makes

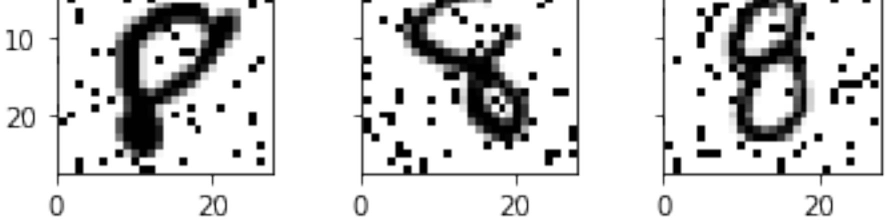
In [12]:

```
import random



FP= list()
FN = list()
for i in range(len(y_test)):
    if predict[i]==1 and y_test[i]!=predict[i]:
        FP.append(i)
    if predict[i]==0 and y_test[i]!=predict[i]:
        FN.append(i)
```

```
fp9 = random.sample(FP,9)
sample_images = x_test[fp9]

plt.clf()
plt.style.use('seaborn-muted')

fig, axes = plt.subplots(3,3,
                         figsize=(5,5),
                         sharex=True, sharey=True,
                         subplot_kw=dict(adjustable='box', aspect='

for i in range(9):

    # axes (subplot) objects are stored in 2d array, accessed with
    subplot_row = i//3
    subplot_col = i%3
    ax = axes[subplot_row, subplot_col]

    # plot image on subplot
    plottable_image = sample_images[i].reshape((28,28))
    ax.imshow(plottable_image, cmap='gray_r',vmin = 0.0,vmax = 1.0)

    ax.set_title('Digit Label: {}'.format(fp9[i]))
    ax.set_xbound([0,28])

plt.tight_layout()
plt.show()
```

```
<Figure size 432x288 with 0 Axes>
```



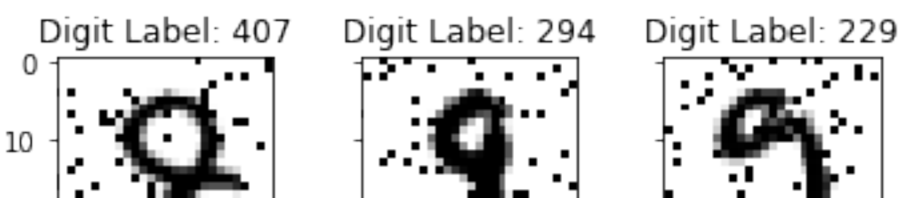


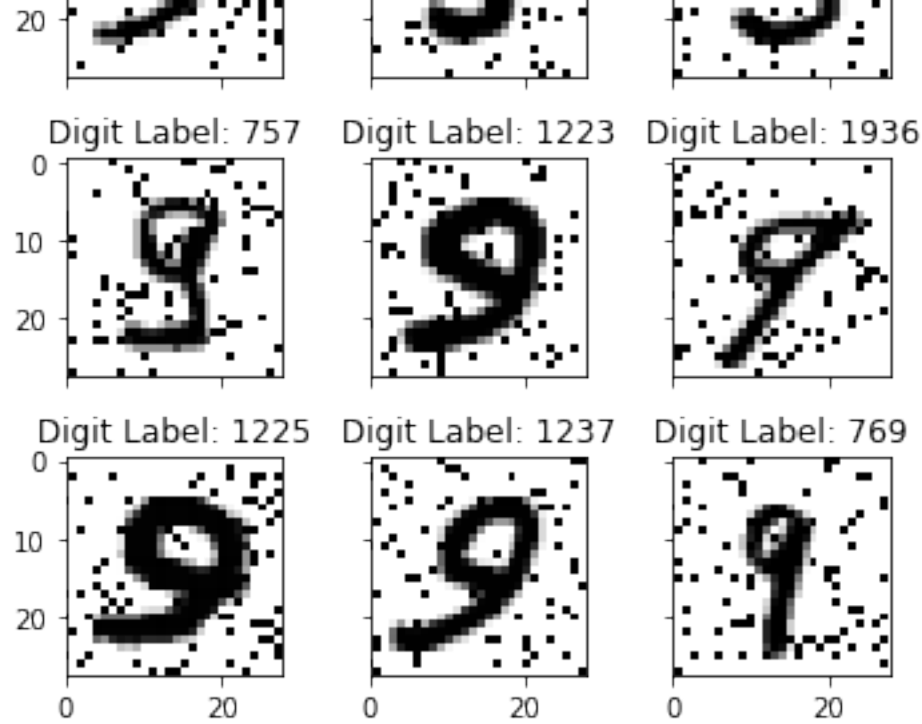
Obviously, we can see that digit #174 was falsely classified as FP.

In [11]:

```
fn9 = random.sample(FN,9)
sample_images = x_test[fn9]

plt.clf()
plt.style.use('seaborn-muted')

fig, axes = plt.subplots(3,3,
                         figsize=(5,5),
                         sharex=True, sharey=True,
                         subplot_kw=dict(adjustable='box', aspect='

for i in range(9):

    # axes (subplot) objects are stored in 2d array, accessed with
    subplot_row = i//3
    subplot_col = i%3
    ax = axes[subplot_row, subplot_col]

    # plot image on subplot
    plottable_image = sample_images[i].reshape((28,28))
    ax.imshow(plottable_image, cmap='gray_r',vmin = 0.0,vmax = 1.0)

    ax.set_title('Digit Label: {}'.format(fn9[i]))
    ax.set_xbound([0,28])

plt.tight_layout()
plt.show()
```

```
<Figure size 432x288 with 0 Axes>
```

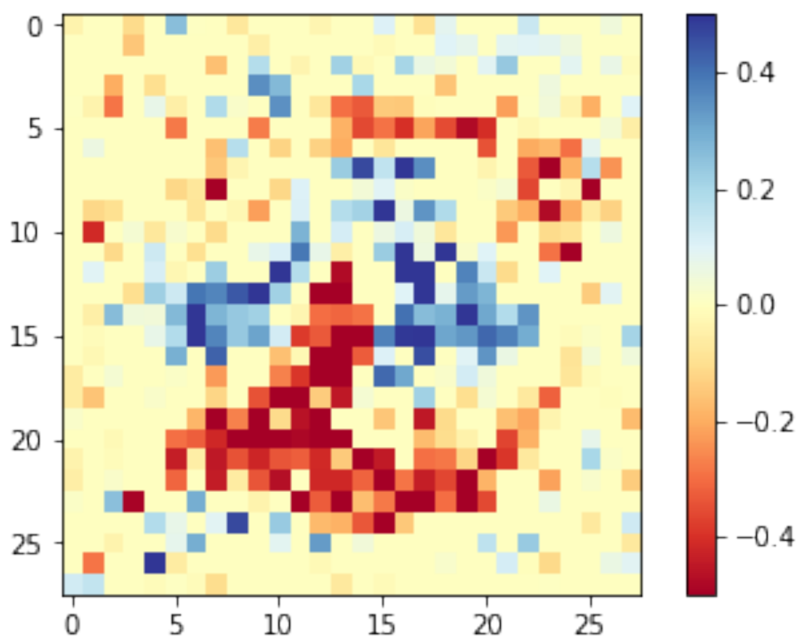




Analyze all of the final weights produced by your classifier

In [13]:

```
w = bestmodel_c.coef_
image = w.reshape((28,28))
plt.imshow(image, cmap='RdYlBu',vmin = -0.5,vmax = 0.5)
plt.colorbar()
plt.show()
```



According to this diverging color map, we could know that the blue part represents positive weights(correspond to 9), and the red part represents negative weights(correspond to 8). The color changes from a heavily saturated to unsaturated means the weight changes towards 0.0. Those weights bring the pixels to 0.0.

In [ ]:

```

```