Binary Classifier Metrics
positive = number of actual positives (count)
negative = number of actual negatives (count)
True Positive = tp = how many samples were correctly classified as positive (count)
True Negative = tn = how many samples were correctly classified as negative (count)
False Positive = fp = how many negative samples were mis-classified as positive (count)
False Negative = fn = how many positive samples were mis-classified as negative (count)

True Positive Rate (TPR, Recall, Probability of detection) = True Positive/Positive
How many positives were correctly classified? (fraction)
Recall value closer to 1 is better. closer to 0 is worse
Example: Radar Operator watching the skies for enemy planes.

Positive Class = Enemy Plane

Negative Class = Friendly Plane

True Positive Rate or Probability of detection – is the probability of correctly classifying an enemy plane </i>

True Negative Rate = True Negative/Negative
How many negatives were correctly classified? (fraction)
True Negative Rate value closer to 1 is better. closer to 0 is worse
True negative rate – is the probability of correctly classifying a friendly plane

False Positive Rate (FPR, Probability of false alarm) = False Positive/Negative
How many negatives were mis-classified as positives (fraction)
False Positive Rate value closer to 0 is better. closer to 1 is worse
Another name for this is Probability of false alarm – is the probability of mis-classifying a friendly plane as an enemy plane

False Negative Rate (FNR, Misses) = False Negative/Positive
How many positives were mis-classified as negative (fraction)
False Negative Rate value closer to 0 is better. closer to 1 is worse
False Negative Rate - is the probability of mis-classifying an enemy plane as a friendly plane

Precision = True Positive/(True Positive + False Positive)
How many positives classified by the algorithm are really positives? (fraction)
Precision value closer to 1 is better. closer to 0 is worse
Precision would go up as enemy planes are correctly identified, while minimizing false alarm

Accuracy = (True Positive + True Negative)/(Positive + Negative)
How many positives and negatives were correctly classified? (fraction)
Accuracy value closer to 1 is better. closer to 0 is worse
Accuracy would go up when enemy planes and friendly planes are correctly identified

```
F1 Score = harmonic mean of Precision and Recall = 2*Precision*Recall /
(Precision + Recall)
F1 Score closer to 1 is better. Closer to 0 is worse.
Reference:
Harmonic Mean - https://en.wikipedia.org/wiki/Harmonic_mean
Confusion Matrix - https://en.wikipedia.org/wiki/Confusion_matrix
```

In [ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import itertools
```

Exam Result Data set

Columns Pass = Actual Pass or Fail for the sample. Pass=1, Fail=0 Model1_Prediction = Predicted Pass or Fail by model 1 Model2_Prediction = Predicted Pass or Fail by model 2 Model3_Prediction = Predicted Pass or Fail by model 3 Model4_Prediction = Predicted Pass or Fail by model 4 We are going to compare performance of these four models

Hours Spent and Exam Result (Pass/Fail) Data set: https://en.wikipedia.org/wiki/Logistic_regression (https://en.wikipedia.org/wiki/Logistic_regression)

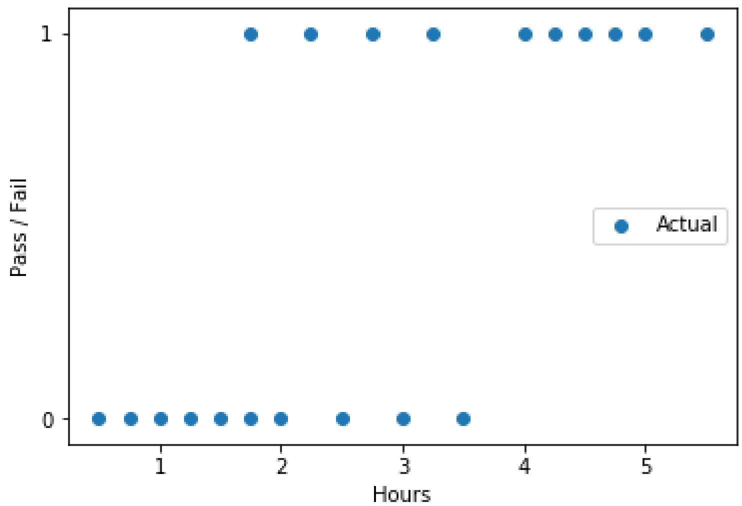
In [3]:
```
models = ['Model 1','Model 2', 'Model 3', 'Model 4']
df = pd.read_csv(r'C:\Users\309962\Desktop\HoursExamSample.csv')
```

In [4]:
```
df
```

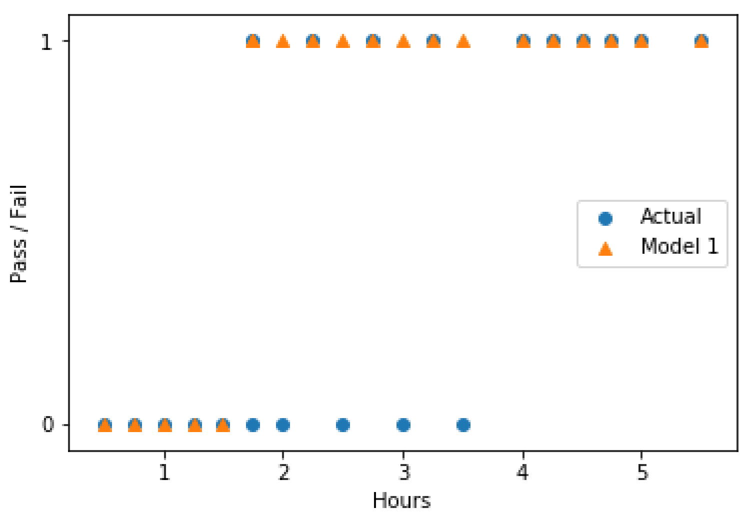
Out[4]:

	Hours	Pass	Model1_Prediction	Model2_Prediction	Model3_Prediction	Model4_Prediction
0	0.50	0	0	0	0	1
1	0.75	0	0	0	0	1
2	1.00	0	0	0	0	1
3	1.25	0	0	0	0	1
4	1.50	0	0	0	0	1
5	1.75	0	1	0	0	1
6	1.75	1	1	0	0	1
7	2.00	0	1	0	0	1
8	2.25	1	1	0	0	1
9	2.50	0	1	0	0	1
10	2.75	1	1	0	0	1
11	3.00	0	1	0	0	1
12	3.25	1	1	0	1	1
13	3.50	0	1	0	1	1
14	4.00	1	1	0	1	1
15	4.25	1	1	0	1	1
16	4.50	1	1	0	1	1
17	4.75	1	1	0	1	1
18	5.00	1	1	0	1	1
19	5.50	1	1	0	1	1

In [5]:
```
plt.figure()
plt.scatter(df['Hours'],df['Pass'],label='Actual')
plt.legend(loc=7)
plt.yticks([0,1])
plt.xlabel('Hours')
plt.ylabel('Pass / Fail')
plt.show()
```



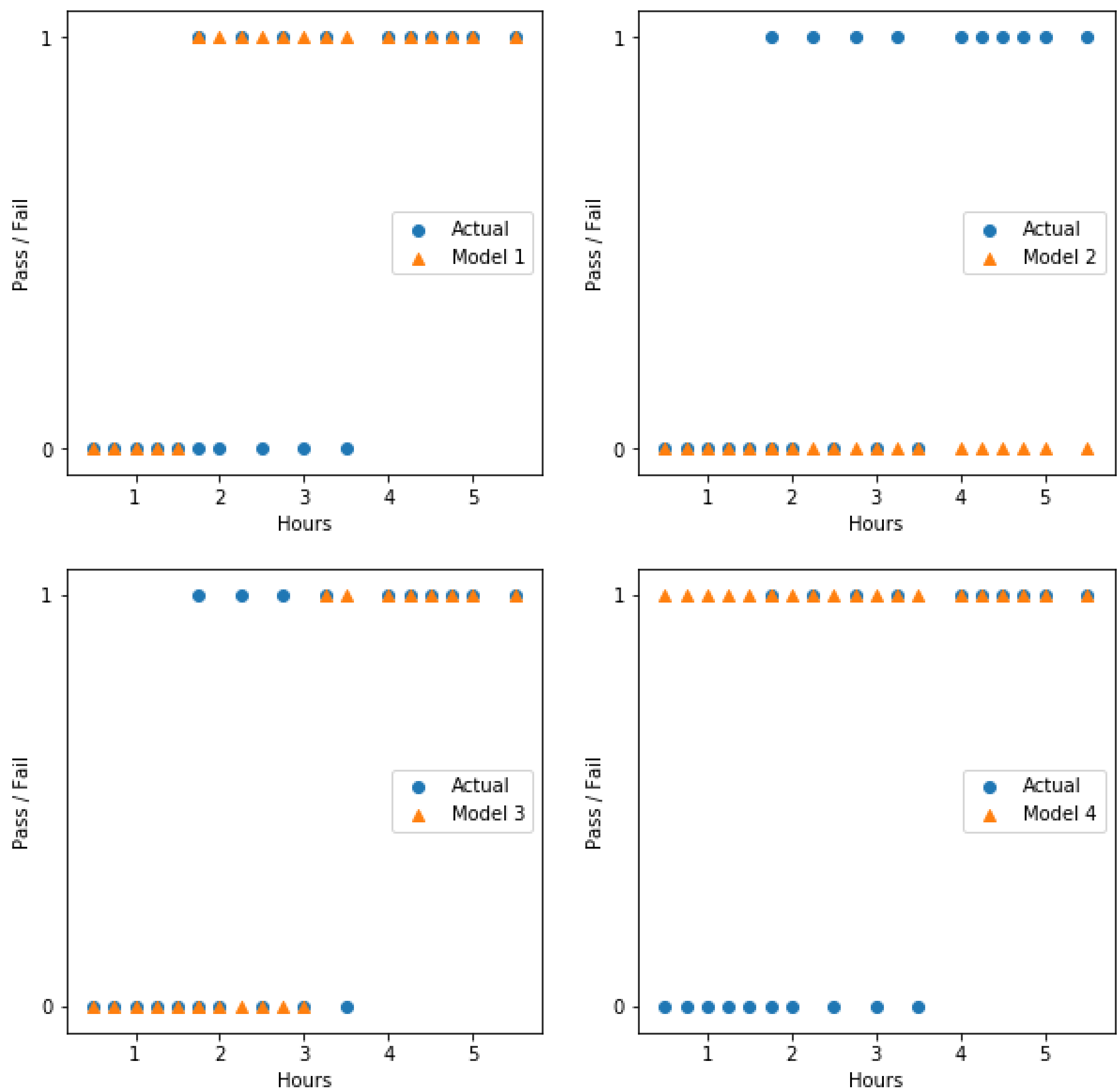
In [6]:
```
# Compare performance of Actual and Model 1 Prediction
plt.figure()
plt.scatter(df['Hours'],df['Pass'],label='Actual')
plt.scatter(df['Hours'],df['Model1_Prediction'],label='Model 1',marker='^')
plt.legend(loc=7)
plt.yticks([0,1])
plt.xlabel('Hours')
plt.ylabel('Pass / Fail')
plt.show()
```



In [7]:
```
plt.figure(figsize=(10,10))

for idx, model in enumerate(models):
    plt.subplot(2,2,idx+1)

    plt.scatter(df['Hours'],df['Pass'],label='Actual')
    plt.scatter(df['Hours'],df[model.replace(' ','') + '_Prediction'],
                label=model,marker='^')
    plt.yticks([0,1])
    plt.legend(loc=7)
    plt.xlabel('Hours')
    plt.ylabel('Pass / Fail')
```



From the plots, we can observe that:

Model 1 is classifying samples as Pass if hours spent studying is greater than 1.5 hours Model 2 is classifying all samples as Fail Model 3 is classifying samples as Pass if hours spent studying is around 3 hours or more Model 4 is classfying all samples as Pass

```
Confusion Matrix
Confusion Matrix is a table that summarizes performance of classification
model.

It summarizes predictions into four categories:
True Positive = tp = how many samples were correctly classified as positive
(count)
True Negative = tn = how many samples were correctly classified as negative
(count)
False Positive = fp = how many negative samples were mis-classified as positive
(count)
False Negative = fn = how many positive samples were mis-classified as negative
(count)

Using these four metrics, we can derive other useful metrics like Recall,
Precision, Accuracy, F1-Score and so forth.

Reference:
https://en.wikipedia.org/wiki/Confusion_matrix
```

In [8]:
```
from sklearn.metrics import classification_report, confusion_matrix
```

In [9]:
```
# Compute confusion matrix
# Compare Actual Vs Model 1 Predictions
cnf_matrix = confusion_matrix(df['Pass'],df['Model1_Prediction'],labels=[1,0])
```

In [10]:
```
cnf_matrix
```

Out[10]:
```
array([[10,  0],
       [ 5,  5]], dtype=int64)
```

In [11]:
```
# Reference: https://scikit-learn.org/stable/modules/model_evaluation.html
# Explicitly stating labels. Pass=1, Fail=0
def true_positive(y_true, y_pred):
    return confusion_matrix(y_true, y_pred,labels=[1,0])[0, 0]

def true_negative(y_true, y_pred):
    return confusion_matrix(y_true,y_pred,labels=[1,0])[1, 1]

def false_positive(y_true, y_pred):
    return confusion_matrix(y_true, y_pred,labels=[1,0])[1, 0]

def false_negative(y_true, y_pred):
    return confusion_matrix(y_true, y_pred,labels=[1,0])[0, 1]
```

In [12]:
```
# Compute Binary Classifier Metrics
# Returns a dictionary {"MetricName":Value,...}

def binary_classifier_metrics(y_true, y_pred):
    metrics = {}

    # References:
    #  https://docs.aws.amazon.com/machine-learning/latest/dg/binary-classificati
    #  https://en.wikipedia.org/wiki/Confusion_matrix

    # Definition:
    # true positive = tp = how many samples were correctly classified as positive
    # true negative = tn = how many samples were correctly classified as negative
    # false positive = fp = how many negative samples were mis-classified as posi
    # false_negative = fn = how many positive samples were mis-classified as nega

    # positive = number of positive samples (count)
    #          = true positive + false negative
    # negative = number of negative samples (count)
    #          = true negative + false positive

    tp = true_positive(y_true, y_pred)
    tn = true_negative(y_true, y_pred)
    fp = false_positive(y_true, y_pred)
    fn = false_negative(y_true, y_pred)

    positive = tp + fn
    negative = tn + fp

    metrics['TruePositive'] = tp
    metrics['TrueNegative'] = tn
    metrics['FalsePositive'] = fp
    metrics['FalseNegative'] = fn

    metrics['Positive'] = positive
    metrics['Negative'] = negative

    # True Positive Rate (TPR, Recall) = true positive/positive
    # How many positives were correctly classified? (fraction)
    # Recall value closer to 1 is better. closer to 0 is worse
    if tp == 0:
        recall = 0
    else:
        recall = tp/positive

    metrics['Recall'] = recall

    # True Negative Rate = True Negative/negative
    # How many negatives were correctly classified? (fraction)
    # True Negative Rate value closer to 1 is better. closer to 0 is worse
    if tn == 0:
        tnr = 0
    else:
        tnr = tn/(negative)
    metrics['TrueNegativeRate'] = tnr
```

```
    # Precision = True Positive/(True Positive + False Positive)
    # How many positives classified by the algorithm are really positives? (fract
    # Precision value closer to 1 is better. closer to 0 is worse
    if tp == 0:
        precision = 0
    else:
        precision = tp/(tp + fp)
    metrics['Precision'] = precision

    # Accuracy = (True Positive + True Negative)/(total positive + total negative
    # How many positives and negatives were correctly classified? (fraction)
    # Accuracy value closer to 1 is better. closer to 0 is worse
    accuracy = (tp + tn)/(positive + negative)
    metrics['Accuracy'] = accuracy

    # False Positive Rate (FPR, False Alarm) = False Positive/(total negative)
    # How many negatives were mis-classified as positives (fraction)
    # False Positive Rate value closer to 0 is better. closer to 1 is worse
    if fp == 0:
        fpr = 0
    else:
        fpr = fp/(negative)
    metrics['FalsePositiveRate'] = fpr

    # False Negative Rate (FNR, Misses) = False Negative/(total Positive)
    # How many positives were mis-classified as negative (fraction)
    # False Negative Rate value closer to 0 is better. closer to 1 is worse
    fnr = fn/(positive)
    metrics['FalseNegativeRate'] = fnr

    # F1 Score = harmonic mean of Precision and Recall
    # F1 Score closer to 1 is better. Closer to 0 is worse.
    if precision == 0 or recall == 0:
        f1 = 0
    else:
        f1 = 2*precision*recall/(precision+recall)

    metrics['F1'] = f1

    return metrics
```

In [13]:
```python
# Reference:
# https://scikit-learn.org/stable/auto_examples/model_selection/plot_confusion_ma
def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        #print("Normalized confusion matrix")
    #else:
    #    print('Confusion matrix, without normalization')

    #print(cm)

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.ylabel('True label')
    plt.xlabel('Predicted label')
    plt.tight_layout()
```

In [14]:
```python
# Compute confusion matrix
cnf_matrix = confusion_matrix(df['Pass'],df['Model1_Prediction'],labels=[1,0])
```

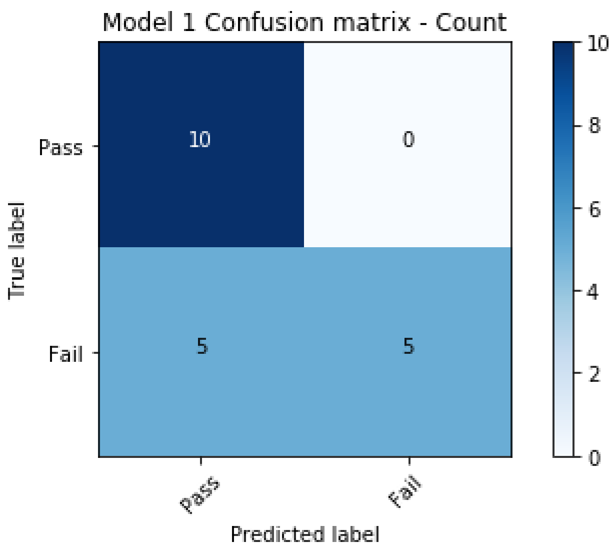
In [15]:
```python
cnf_matrix
```

Out[15]:
```
array([[10,  0],
       [ 5,  5]], dtype=int64)
```

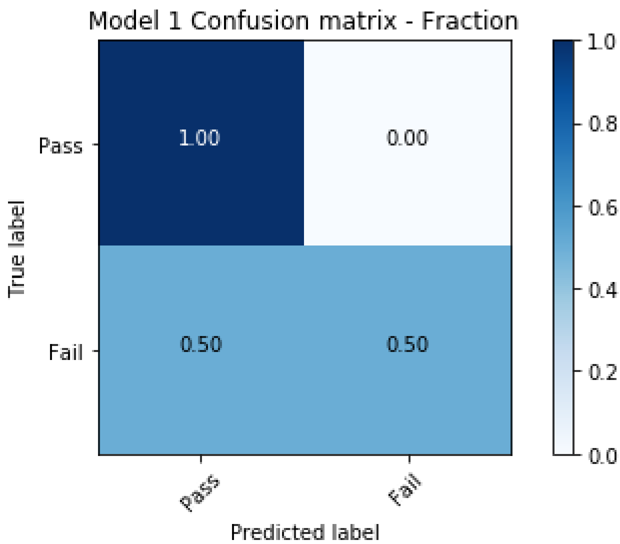
In [16]:
```
print('TP:',true_positive(df['Pass'],df['Model1_Prediction']))
print('TN:',true_negative(df['Pass'],df['Model1_Prediction']))
print('FP:',false_positive(df['Pass'],df['Model1_Prediction']))
print('FN:',false_negative(df['Pass'],df['Model1_Prediction']))
```

```
TP: 10
TN: 5
FP: 5
FN: 0
```

In [17]:
```
# Plot confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=['Pass','Fail'],
                      title='Model 1 Confusion matrix - Count')
```

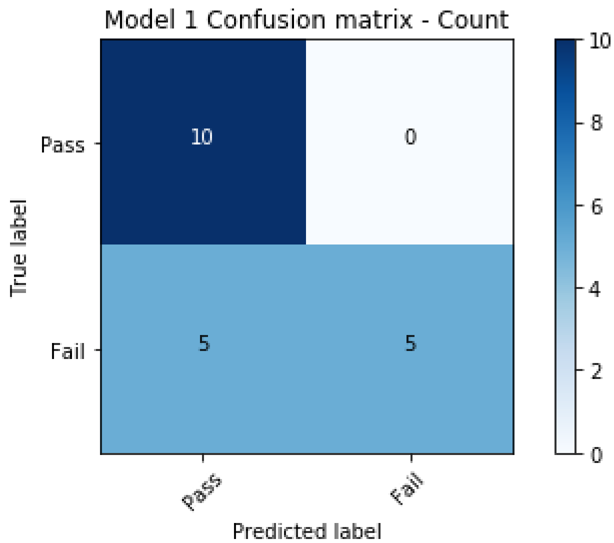


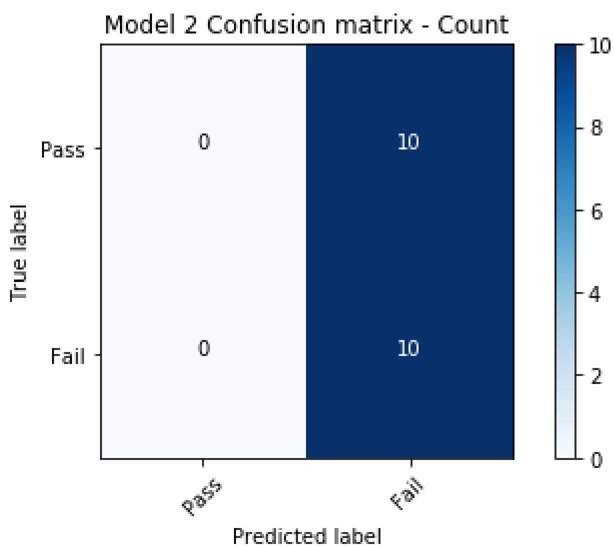
In [18]:
```
# Plot normalized confusion matrix (numbers are shown as a fraction)
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=['Pass','Fail'],
                      title='Model 1 Confusion matrix - Fraction',normalize=True)
```

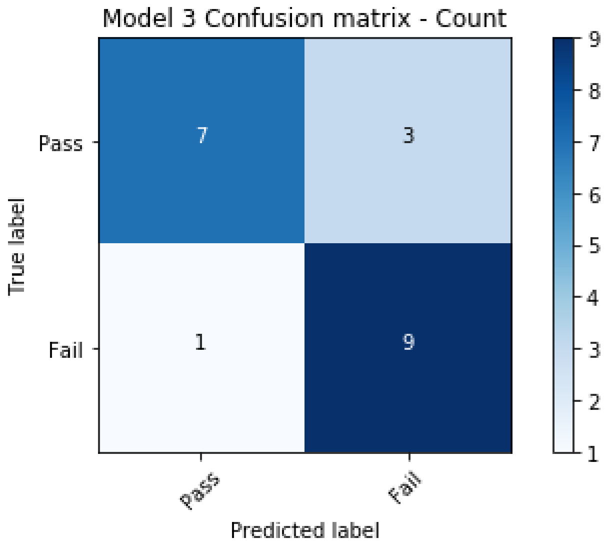


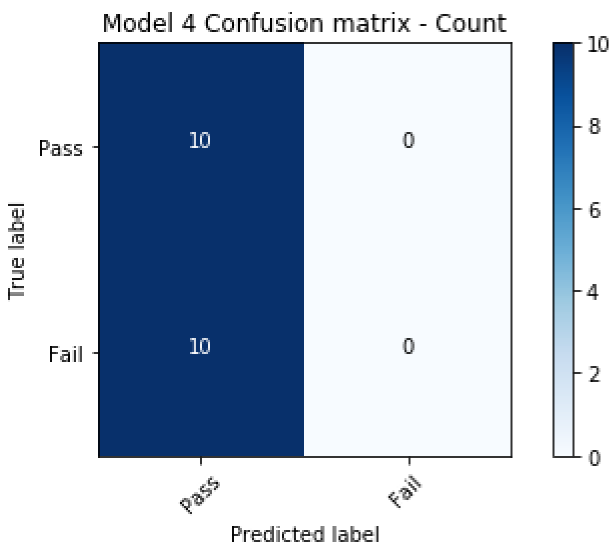
In [19]:
```
# Plot confusion matrix
# Show actual counts
for model in models:
    #print(model)
    cnf_matrix = confusion_matrix(df['Pass'],
                                  df[model.replace(' ','') + '_Prediction'],label
    np.set_printoptions(precision=2)

    # Plot non-normalized confusion matrix
    plt.figure()
    plot_confusion_matrix(cnf_matrix, classes=['Pass','Fail'],
                          title= model + ' Confusion matrix - Count', normalize=False
```



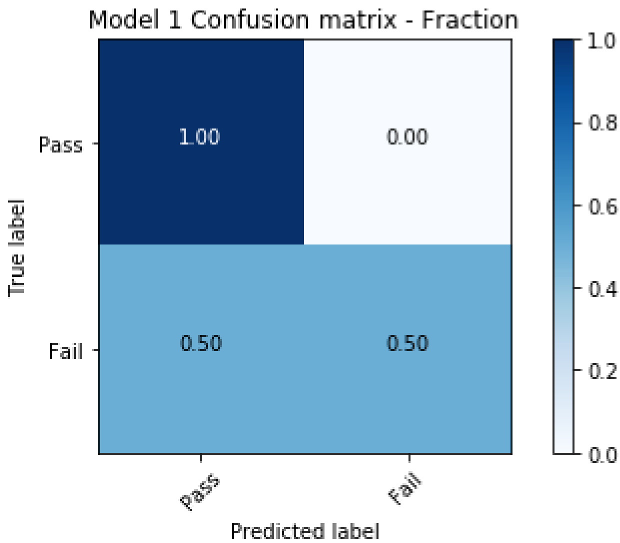


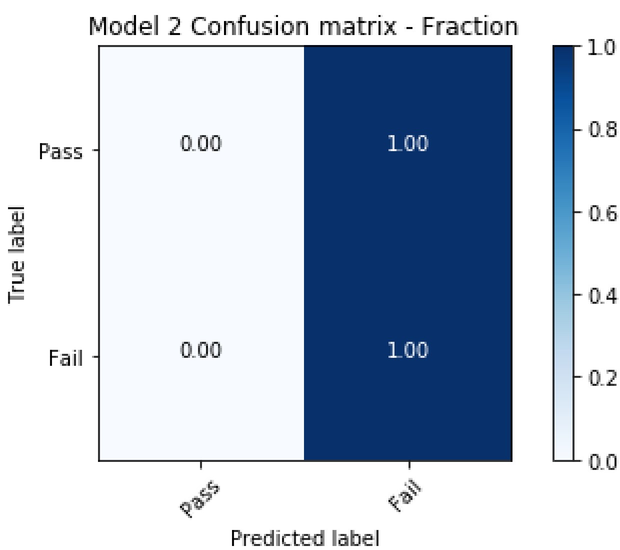

Model 3 Confusion matrix - Count
Pass
Fail
True label
7
3
1
9
Pass
Fail
Predicted label
9
8
7
6
5
4
3
2
1

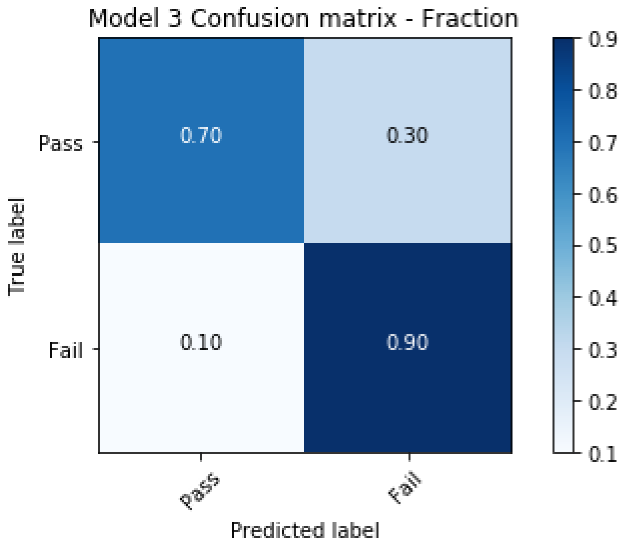

Model 4 Confusion matrix - Count
Pass
Fail
True label
10
0
10
0
Pass
Fail
Predicted label
10
8
6
4
2
0

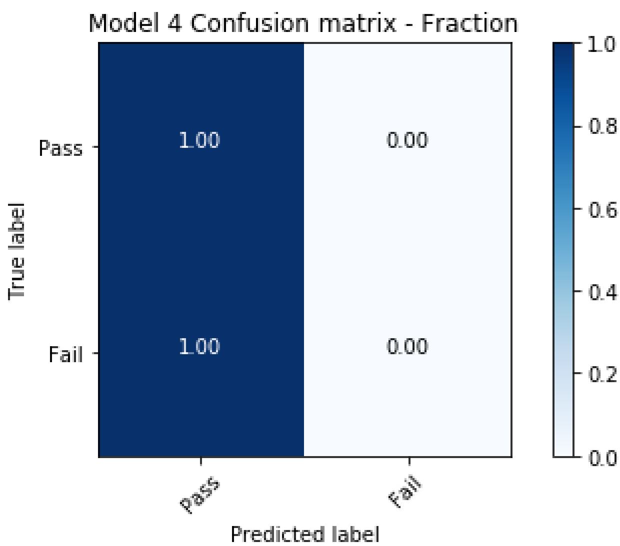
In [20]:
```
# Compute confusion matrix
# Show Fraction
for model in models:
    #print(model)
    cnf_matrix = confusion_matrix(df['Pass'],
                                  df[model.replace(' ','') + '_Prediction'],label
    np.set_printoptions(precision=2)

    # Plot non-normalized confusion matrix
    plt.figure()
    plot_confusion_matrix(cnf_matrix, classes=['Pass','Fail'],
                          title= model + ' Confusion matrix - Fraction', normalize=Tr
```









In [21]:

```
# Compute Metrics for all models
all_metrics = []
for model in models:
    print(model)
    colname = model.replace(' ','') + '_Prediction'

    metrics = binary_classifier_metrics(df['Pass'],df[colname])
    all_metrics.append(metrics)
```

```
Model 1
Model 2
Model 3
Model 4
```

In [22]:

```

# Create a metrics dataframe
# https://stackoverflow.com/questions/41168558/python-how-to-convert-json-file-to
df_metrics=pd.DataFrame.from_dict(all_metrics)
df_metrics.index = models
```

In [23]:

```
print('Counts')
print(df_metrics[['TruePositive',
                  'FalseNegative',
                  'FalsePositive',
                  'TrueNegative',]].round(2))
print()
print('Ratios')
print(df_metrics[['Recall',
                  'FalseNegativeRate',
                  'FalsePositiveRate',
                  'TrueNegativeRate',]].round(2))
print()

print(df_metrics[['Precision',
                  'Accuracy',
                  'F1']].round(2))
```

```
Counts
         TruePositive  FalseNegative  FalsePositive  TrueNegative
Model 1            10              0              5             5
Model 2             0             10              0            10
Model 3             7              3              1             9
Model 4            10              0             10             0

Ratios
         Recall  FalseNegativeRate  FalsePositiveRate  TrueNegativeRate
Model 1     1.0                0.0                0.5               0.5
Model 2     0.0                1.0                0.0               1.0
Model 3     0.7                0.3                0.1               0.9
Model 4     1.0                0.0                1.0               0.0

         Precision  Accuracy    F1
Model 1       0.67      0.75  0.80
Model 2       0.00      0.50  0.00
Model 3       0.88      0.80  0.78
Model 4       0.50      0.50  0.67
```

In [24]:
```
# Using SKLearn classification report
# Micro Average Vs Macro Average
# https://datascience.stackexchange.com/questions/15989/micro-average-vs-macro-av
for model in models:
    print(model)
    print(classification_report(
    df['Pass'],
    df[model.replace(' ','') + '_Prediction'],
    labels=[1,0],
    target_names=['Pass','Fail']))
```

```
Model 1
             precision    recall  f1-score   support

       Pass       0.67      1.00      0.80        10
       Fail       1.00      0.50      0.67        10

avg / total       0.83      0.75      0.73        20

Model 2
             precision    recall  f1-score   support

       Pass       0.00      0.00      0.00        10
       Fail       0.50      1.00      0.67        10

avg / total       0.25      0.50      0.33        20

Model 3
             precision    recall  f1-score   support

       Pass       0.88      0.70      0.78        10
       Fail       0.75      0.90      0.82        10

avg / total       0.81      0.80      0.80        20

Model 4
             precision    recall  f1-score   support

       Pass       0.50      1.00      0.67        10
       Fail       0.00      0.00      0.00        10

avg / total       0.25      0.50      0.33        20


C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics\classification.py:11
35: UndefinedMetricWarning: Precision and F-score are ill-defined and being set
to 0.0 in labels with no predicted samples.
  'precision', 'predicted', average, warn_for)
```

```
Summary
From these metrics, we can see that Model 1 and Model 3 are performing better
than Model 2 and 4.
Model 1 has higher Recall (it correctly identifies more positive samples) at
the cost of higher False Positive Rate (negative samples were misclassified as
positive)
```

```
Model 3 offers balanced performance
```