In [1]:

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
import matplotlib.pylab as plt
import numpy as np
import itertools
import seaborn as sb
import keras
from scipy import stats
from keras.models import Sequential
from keras.layers import Dense, Dropout, Activation
from keras.callbacks import ModelCheckpoint

%matplotlib inline
```

In [2]:

```
credit_df = pd.read_csv( "german-credit-card.txt", delim_whitespace = True, head
er = None)
```

In [3]:

```
credit_df.head()
```

Out[3]:

	0	1	2	3	4	5	6	7	8	9	...	11	12	13	14	15	16
0	A11	6	A34	A43	1169	A65	A75	4	A93	A101	...	A121	67	A143	A152	2	A173
1	A12	48	A32	A43	5951	A61	A73	2	A92	A101	...	A121	22	A143	A152	1	A173
2	A14	12	A34	A46	2096	A61	A74	2	A93	A101	...	A121	49	A143	A152	1	A172
3	A11	42	A32	A42	7882	A61	A74	2	A93	A103	...	A122	45	A143	A153	1	A173
4	A11	24	A33	A40	4870	A61	A73	3	A93	A101	...	A124	53	A143	A153	2	A173

5 rows × 21 columns

In [4]:

```
columns = ['checkin_acc', 'duration', 'credit_history', 'purpose', 'amount',
           'saving_acc', 'present_emp_since', 'inst_rate', 'personal_status',
           'other_debtors', 'residing_since', 'property', 'age',
           'inst_plans', 'housing', 'num_credits',
           'job', 'dependents', 'telephone', 'foreign_worker', 'status']
```

In [5]:

```
credit_df.columns = columns
```

In [6]:

```
credit_df = pd.get_dummies(credit_df, drop_first = True)
credit_df
```

Out[6]:

	duration	amount	inst_rate	residing_since	age	num_credits	dependents	status	che
0	6	1169	4	4	67	2	1	1	
1	48	5951	2	2	22	1	1	2	
2	12	2096	2	3	49	1	2	1	
3	42	7882	2	4	45	1	2	1	
4	24	4870	3	4	53	2	2	2	
...	...	...	...	...	...	...	...	...	
995	12	1736	3	4	31	1	1	1	
996	30	3857	4	4	40	1	1	1	
997	12	804	4	4	38	1	1	1	
998	45	1845	4	4	23	1	1	2	
999	45	4576	3	4	27	1	1	1	

1000 rows × 49 columns

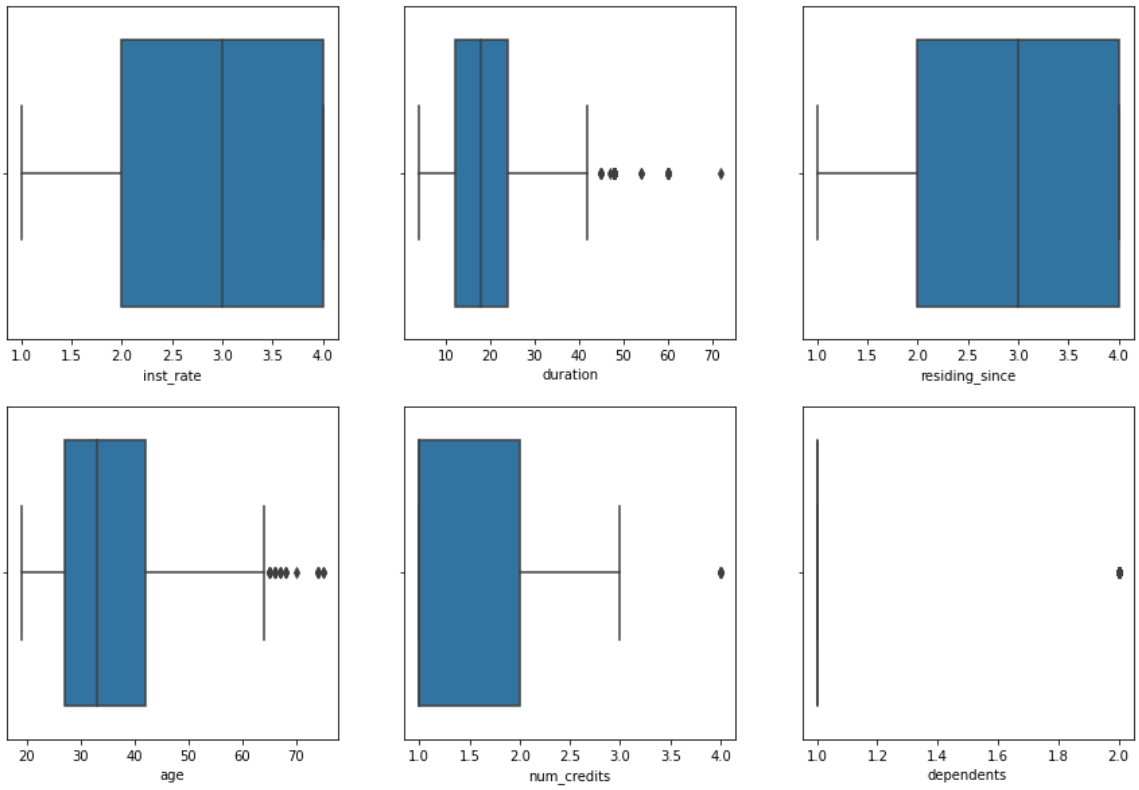
In [8]:

```
credit_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 49 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   duration               1000 non-null   int64
 1   amount                 1000 non-null   int64
 2   inst_rate              1000 non-null   int64
 3   residing_since         1000 non-null   int64
 4   age                    1000 non-null   int64
 5   num_credits            1000 non-null   int64
 6   dependents             1000 non-null   int64
 7   status                 1000 non-null   int64
 8   checkin_acc_A12        1000 non-null   uint8
 9   checkin_acc_A13        1000 non-null   uint8
 10  checkin_acc_A14        1000 non-null   uint8
 11  credit_history_A31     1000 non-null   uint8
 12  credit_history_A32     1000 non-null   uint8
 13  credit_history_A33     1000 non-null   uint8
 14  credit_history_A34     1000 non-null   uint8
 15  purpose_A41            1000 non-null   uint8
 16  purpose_A410           1000 non-null   uint8
 17  purpose_A42            1000 non-null   uint8
 18  purpose_A43            1000 non-null   uint8
 19  purpose_A44            1000 non-null   uint8
 20  purpose_A45            1000 non-null   uint8
 21  purpose_A46            1000 non-null   uint8
 22  purpose_A48            1000 non-null   uint8
 23  purpose_A49            1000 non-null   uint8
 24  saving_acc_A62         1000 non-null   uint8
 25  saving_acc_A63         1000 non-null   uint8
 26  saving_acc_A64         1000 non-null   uint8
 27  saving_acc_A65         1000 non-null   uint8
 28  present_emp_since_A72  1000 non-null   uint8
 29  present_emp_since_A73  1000 non-null   uint8
 30  present_emp_since_A74  1000 non-null   uint8
 31  present_emp_since_A75  1000 non-null   uint8
 32  personal_status_A92    1000 non-null   uint8
 33  personal_status_A93    1000 non-null   uint8
 34  personal_status_A94    1000 non-null   uint8
 35  other_debtors_A102     1000 non-null   uint8
 36  other_debtors_A103     1000 non-null   uint8
 37  property_A122          1000 non-null   uint8
 38  property_A123          1000 non-null   uint8
 39  property_A124          1000 non-null   uint8
 40  inst_plans_A142        1000 non-null   uint8
 41  inst_plans_A143        1000 non-null   uint8
 42  housing_A152           1000 non-null   uint8
 43  housing_A153           1000 non-null   uint8
 44  job_A172               1000 non-null   uint8
 45  job_A173               1000 non-null   uint8
 46  job_A174               1000 non-null   uint8
 47  telephone_A192         1000 non-null   uint8
 48  foreign_worker_A202    1000 non-null   uint8
dtypes: int64(8), uint8(41)
memory usage: 102.7 KB
```

In [9]:

```
fig, axes = plt.subplots(2,3,figsize=(15,10))

sb.boxplot(x="inst_rate", data=credit_df, ax=axes[0, 0])
sb.boxplot(x="duration", data=credit_df, ax=axes[0, 1])
sb.boxplot(x="residing_since", data=credit_df, ax=axes[0, 2])
sb.boxplot(x="age", data=credit_df, ax=axes[1, 0])
sb.boxplot(x="num_credits", data=credit_df, ax=axes[1, 1])
sb.boxplot(x="dependents", data=credit_df, ax=axes[1, 2])


plt.show()
```

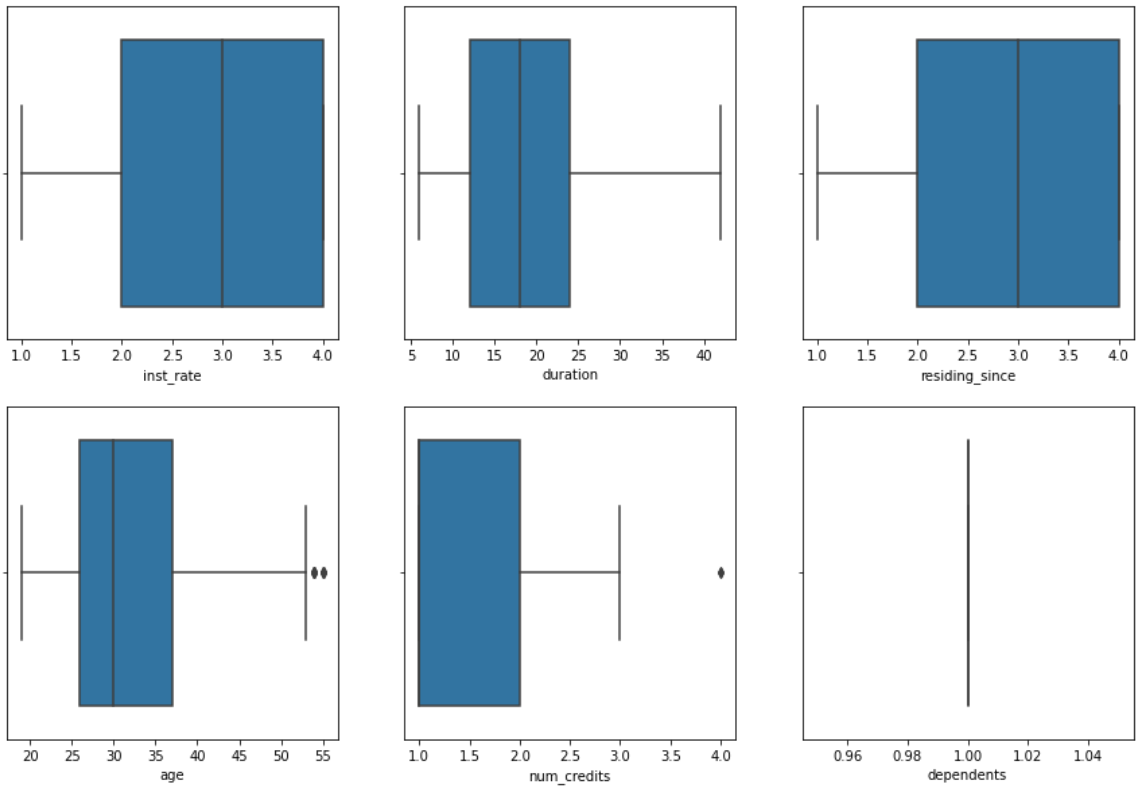


In [10]:

```
credit_df = credit_df[credit_df.duration <= 43]
credit_df = credit_df[credit_df.age <= 55]
credit_df = credit_df[credit_df.dependents <= 1]
# X = X[X.duration <= 43]
```

In [11]:

```
fig, axes = plt.subplots(2,3,figsize=(15,10))

sb.boxplot(x="inst_rate", data=credit_df, ax=axes[0, 0])
sb.boxplot(x="duration", data=credit_df, ax=axes[0, 1])
sb.boxplot(x="residing_since", data=credit_df, ax=axes[0, 2])
sb.boxplot(x="age", data=credit_df, ax=axes[1, 0])
sb.boxplot(x="num_credits", data=credit_df, ax=axes[1, 1])
sb.boxplot(x="dependents", data=credit_df, ax=axes[1, 2])


plt.show()
```



In [12]:

```
corr_analysis = credit_df.corr()
```

In [13]:

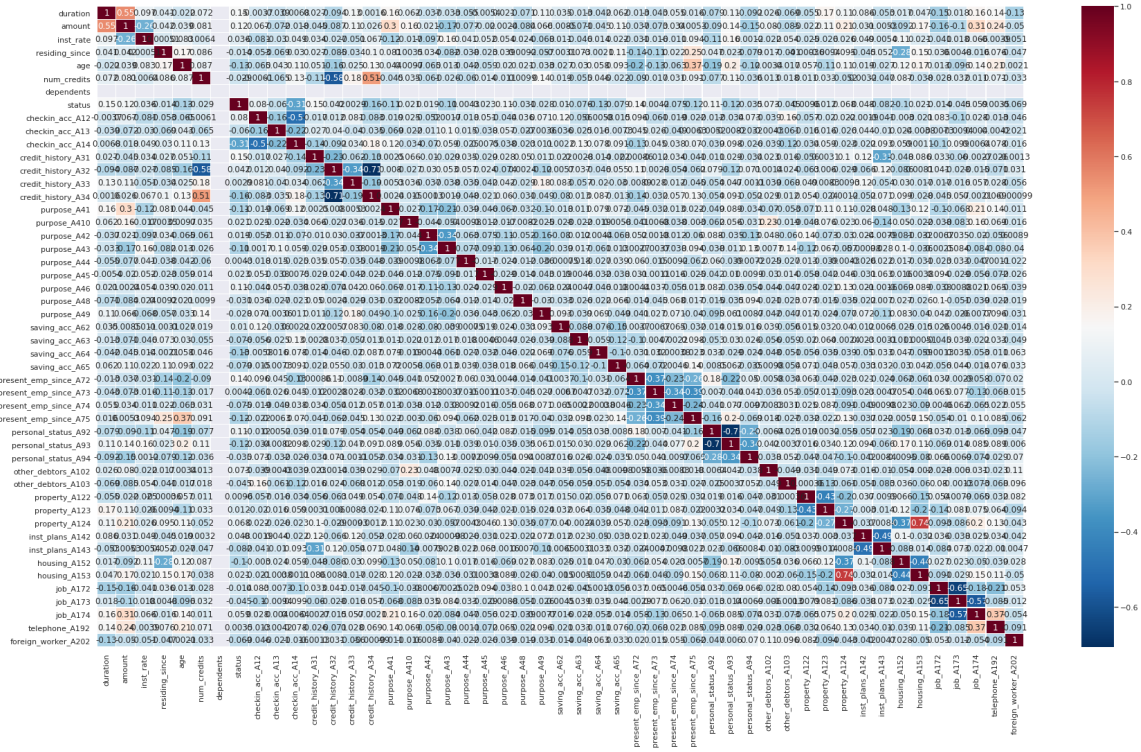
```
sb.set(rc={"figure.figsize":(30,17)})
```

In [14]:

```
sb.heatmap(corr_analysis,
           xticklabels=corr_analysis.columns,
           yticklabels=corr_analysis.columns,
           cmap='RdBu_r',
           annot=True,
           linewidth=0.1)
```

Out[14]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe122ecbf28>
```



In [15]:

```
max_duration = np.amax(credit_df["duration"])
max_amount = np.amax(credit_df["amount"])
max_inst_rate = np.amax(credit_df["inst_rate"])
max_residing_since = np.amax(credit_df["residing_since"])
max_dependents = np.amax(credit_df["dependents"])
max_age = np.amax(credit_df["age"])
max_num_credits = np.amax(credit_df["num_credits"])
```

In [16]:

```
# Dividing each feature with it's maximum value
credit_df["duration"] = credit_df["duration"]/max_duration
credit_df["amount"] = credit_df["amount"]/max_amount
credit_df["inst_rate"] = credit_df["inst_rate"]/max_inst_rate
credit_df["residing_since"] = credit_df["residing_since"]/max_residing_since
credit_df["dependents"] = credit_df["dependents"]/max_dependents
credit_df["age"] = credit_df["age"]/max_age
credit_df["num_credits"] = credit_df["num_credits"]/max_num_credits
```

In [17]:

```
Y = credit_df.status - 1
X = credit_df.drop("status", axis=1)
```

In [103]:

```
X_train, X_test, y_train, y_test = train_test_split( X, Y, test_size = 0.027, ra
ndom_state = 2 )
print("Training Data Size: ", X_train.shape[0])
print("Testing Data Size: ", X_test.shape[0])
```

```
Training Data Size:  706
Testing Data Size:  20
```

In [104]:

```
X_train = np.array(X_train)
y_train = np.array(keras.utils.to_categorical(y_train, 2))
X_test = np.array(X_test)
y_test = np.array(keras.utils.to_categorical(y_test, 2))

print(X_train[:10])
print(y_train[:10])
```

```
[[0.29 0.03 0.75 0.75 0.76 0.5  1.   0.   1.   0.   1.   0.   0.
0.
  0.   0.   0.   1.   0.   0.   0.   0.   0.   0.   0.   1.   0.
0.
  1.   0.   0.   1.   0.   0.   0.   0.   0.   0.   0.   0.   1.
0.
  0.   0.   1.   0.   0.   0.  ]
 [0.24 0.12 0.25 1.   0.69 0.25 1.   0.   0.   1.   0.   1.   0.
0.
  0.   0.   0.   1.   0.   0.   0.   0.   0.   0.   0.   0.   0.
0.
  1.   0.   0.   0.   1.   0.   0.   0.   1.   0.   0.   0.   1.
1.
  0.   0.   1.   0.   1.   1.  ]
 [0.29 0.07 0.75 0.5  0.49 0.5  1.   0.   0.   1.   0.   0.   0.
1.
  0.   0.   0.   0.   0.   0.   0.   0.   1.   0.   0.   0.   0.
0.
  1.   0.   0.   1.   0.   0.   0.   0.   0.   0.   0.   0.   1.
1.
  0.   0.   1.   0.   0.   0.  ]
 [0.57 0.26 0.75 1.   0.51 0.25 1.   1.   0.   0.   0.   1.   0.
0.
  1.   0.   0.   0.   0.   0.   0.   0.   0.   0.   1.   0.   0.
1.
  0.   0.   0.   1.   0.   0.   0.   0.   0.   1.   0.   0.   1.
0.
  0.   0.   1.   0.   0.   0.  ]
 [0.21 0.09 0.75 0.5  0.49 0.25 1.   0.   0.   0.   0.   1.   0.
0.
  0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.
1.
  0.   0.   0.   0.   1.   0.   0.   0.   0.   0.   1.   0.   1.
0.
  1.   0.   0.   1.   1.   0.  ]
 [0.57 0.2  1.   1.   0.42 0.25 1.   0.   0.   0.   0.   1.   0.
0.
  0.   0.   1.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.
1.
  0.   0.   0.   1.   0.   0.   0.   0.   0.   0.   0.   0.   1.
0.
  0.   1.   0.   0.   1.   0.  ]
 [0.14 0.03 1.   1.   0.42 0.25 1.   0.   0.   0.   0.   1.   0.
0.
  0.   0.   0.   0.   0.   0.   1.   0.   0.   0.   0.   0.   0.
1.
  0.   0.   0.   1.   0.   0.   0.   0.   1.   0.   0.   0.   1.
1.
  0.   0.   1.   0.   0.   0.  ]
 [0.29 0.09 1.   0.25 0.6  0.25 1.   0.   1.   0.   0.   1.   0.
0.
  0.   0.   1.   0.   0.   0.   0.   0.   0.   0.   0.   0.   0.
1.
  0.   0.   0.   1.   0.   0.   0.   0.   1.   0.   0.   0.   0.
1.
  0.   0.   0.   1.   1.   0.  ]
 [0.14 0.06 0.75 0.5  0.44 0.25 1.   0.   0.   1.   0.   0.   1.
0.
  0.   0.   0.   1.   0.   0.   0.   0.   0.   0.   0.   0.   0.
0.
  1.   0.   0.   1.   0.   0.   0.   0.   0.   0.   0.   0.   1.
```

```
1.
  0.   0.   1.   0.   0.   0.  ]
 [0.57 0.55 0.5  0.5  0.49 0.5  1.   0.   0.   1.   0.   0.   1.
0.
  0.   0.   0.   0.   0.   0.   0.   0.   1.   0.   0.   0.   0.
1.
  0.   0.   0.   0.   1.   0.   0.   0.   0.   1.   0.   0.   0.
1.
  0.   0.   1.   0.   1.   0.  ]]
[[1. 0.]
 [1. 0.]
 [1. 0.]
 [0. 1.]
 [0. 1.]
 [0. 1.]
 [0. 1.]
 [1. 0.]
 [1. 0.]
 [0. 1.]]
```

In [135]:

```
model = Sequential()

model.add(Dense(256, activation="relu", input_shape=(X_train.shape[1],)))
model.add(Dropout(0.5))
model.add(Dense(128, activation="tanh"))
model.add(Dropout(0.5))
model.add(Dense(128, activation="relu"))
model.add(Dropout(0.5))
model.add(Dense(2, activation="softmax"))


model.compile(loss="categorical_crossentropy", optimizer="adamax", metrics=["acc
uracy"])
model.summary()
```

```
Model: "sequential_11"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_47 (Dense)             (None, 256)               12544
_________________________________________________________________
dropout_36 (Dropout)         (None, 256)               0
_________________________________________________________________
dense_48 (Dense)             (None, 128)               32896
_________________________________________________________________
dropout_37 (Dropout)         (None, 128)               0
_________________________________________________________________
dense_49 (Dense)             (None, 128)               16512
_________________________________________________________________
dropout_38 (Dropout)         (None, 128)               0
_________________________________________________________________
dense_50 (Dense)             (None, 2)                 258
=================================================================
Total params: 62,210
Trainable params: 62,210
Non-trainable params: 0
_________________________________________________________________
```

In [136]:

```
hist = model.fit(X_train, y_train, epochs=25, batch_size=100, validation_split=
0.25,
                 shuffle=True)
```

```
Epoch 1/25
6/6 [==============================] - 0s 28ms/step - loss: 0.6744 -
accuracy: 0.6163 - val_loss: 0.6608 - val_accuracy: 0.6497
Epoch 2/25
6/6 [==============================] - 0s 14ms/step - loss: 0.6021 -
accuracy: 0.7278 - val_loss: 0.6844 - val_accuracy: 0.6497
Epoch 3/25
6/6 [==============================] - 0s 12ms/step - loss: 0.5866 -
accuracy: 0.7391 - val_loss: 0.6638 - val_accuracy: 0.6497
Epoch 4/25
6/6 [==============================] - 0s 13ms/step - loss: 0.5707 -
accuracy: 0.7240 - val_loss: 0.6426 - val_accuracy: 0.6497
Epoch 5/25
6/6 [==============================] - 0s 12ms/step - loss: 0.5873 -
accuracy: 0.7335 - val_loss: 0.6280 - val_accuracy: 0.6497
Epoch 6/25
6/6 [==============================] - 0s 14ms/step - loss: 0.5856 -
accuracy: 0.7240 - val_loss: 0.6195 - val_accuracy: 0.6497
Epoch 7/25
6/6 [==============================] - 0s 11ms/step - loss: 0.5463 -
accuracy: 0.7278 - val_loss: 0.6148 - val_accuracy: 0.6497
Epoch 8/25
6/6 [==============================] - 0s 16ms/step - loss: 0.5565 -
accuracy: 0.7259 - val_loss: 0.6132 - val_accuracy: 0.6497
Epoch 9/25
6/6 [==============================] - 0s 13ms/step - loss: 0.5537 -
accuracy: 0.7410 - val_loss: 0.6117 - val_accuracy: 0.6497
Epoch 10/25
6/6 [==============================] - 0s 11ms/step - loss: 0.5668 -
accuracy: 0.7202 - val_loss: 0.6105 - val_accuracy: 0.6497
Epoch 11/25
6/6 [==============================] - 0s 12ms/step - loss: 0.5455 -
accuracy: 0.7486 - val_loss: 0.6087 - val_accuracy: 0.6497
Epoch 12/25
6/6 [==============================] - 0s 13ms/step - loss: 0.5451 -
accuracy: 0.7316 - val_loss: 0.6051 - val_accuracy: 0.6497
Epoch 13/25
6/6 [==============================] - 0s 13ms/step - loss: 0.5407 -
accuracy: 0.7221 - val_loss: 0.6003 - val_accuracy: 0.6497
Epoch 14/25
6/6 [==============================] - 0s 14ms/step - loss: 0.5359 -
accuracy: 0.7221 - val_loss: 0.5967 - val_accuracy: 0.6497
Epoch 15/25
6/6 [==============================] - 0s 13ms/step - loss: 0.5300 -
accuracy: 0.7391 - val_loss: 0.5949 - val_accuracy: 0.6497
Epoch 16/25
6/6 [==============================] - 0s 12ms/step - loss: 0.5342 -
accuracy: 0.7524 - val_loss: 0.5921 - val_accuracy: 0.6497
Epoch 17/25
6/6 [==============================] - 0s 13ms/step - loss: 0.5236 -
accuracy: 0.7410 - val_loss: 0.5909 - val_accuracy: 0.6497
Epoch 18/25
6/6 [==============================] - 0s 12ms/step - loss: 0.5290 -
accuracy: 0.7391 - val_loss: 0.5874 - val_accuracy: 0.6497
Epoch 19/25
6/6 [==============================] - 0s 13ms/step - loss: 0.5170 -
accuracy: 0.7543 - val_loss: 0.5874 - val_accuracy: 0.6497
Epoch 20/25
6/6 [==============================] - 0s 13ms/step - loss: 0.5092 -
accuracy: 0.7448 - val_loss: 0.5869 - val_accuracy: 0.6554
Epoch 21/25
```

```
6/6 [==============================] - 0s 13ms/step - loss: 0.5165 -
accuracy: 0.7372 - val_loss: 0.5885 - val_accuracy: 0.6554
Epoch 22/25
6/6 [==============================] - 0s 13ms/step - loss: 0.5044 -
accuracy: 0.7486 - val_loss: 0.5858 - val_accuracy: 0.6780
Epoch 23/25
6/6 [==============================] - 0s 13ms/step - loss: 0.5155 -
accuracy: 0.7410 - val_loss: 0.5782 - val_accuracy: 0.6836
Epoch 24/25
6/6 [==============================] - 0s 14ms/step - loss: 0.5091 -
accuracy: 0.7505 - val_loss: 0.5756 - val_accuracy: 0.6836
Epoch 25/25
6/6 [==============================] - 0s 11ms/step - loss: 0.4955 -
accuracy: 0.7543 - val_loss: 0.5785 - val_accuracy: 0.6836
```

In [137]:

```
training_score = model.evaluate(X_train, y_train)
print("\n Training Accuracy:", training_score[1])
testing_score = model.evaluate(X_test, y_test)
print("\n Testing Accuracy:", testing_score[1])
```

```
23/23 [==============================] - 0s 2ms/step - loss: 0.4865
- accuracy: 0.7436

 Training Accuracy: 0.743626058101654
1/1 [==============================] - 0s 1ms/step - loss: 0.4476 -
accuracy: 0.7500

 Testing Accuracy: 0.75
```

In [138]:

```
# plotting accuracy graph
results = model.predict_classes(X_test, verbose=1)
```

```
1/1 [==============================] - 0s 3ms/step
```

In [144]:

```
print("Predicted Results: ")
results
```

```
Predicted Results:
```

Out[144]:

```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0])
```

In [145]:

```
y_real = np.argmax(y_test, axis=-1)
print("Actual Results: ")
y_real
```

```
Actual Results:
```

Out[145]:

```
array([0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0])
```

In [146]:

```
total = 0
# good = 0, bad = 1
for real, pred in zip(y_real, results):
    if real == 0 and pred == 1:
        total = total + 1
    elif real == 1 and pred == 0:
        total = total + 5

print(total)
```

```
17
```

we need to plot some Confusion Matrix

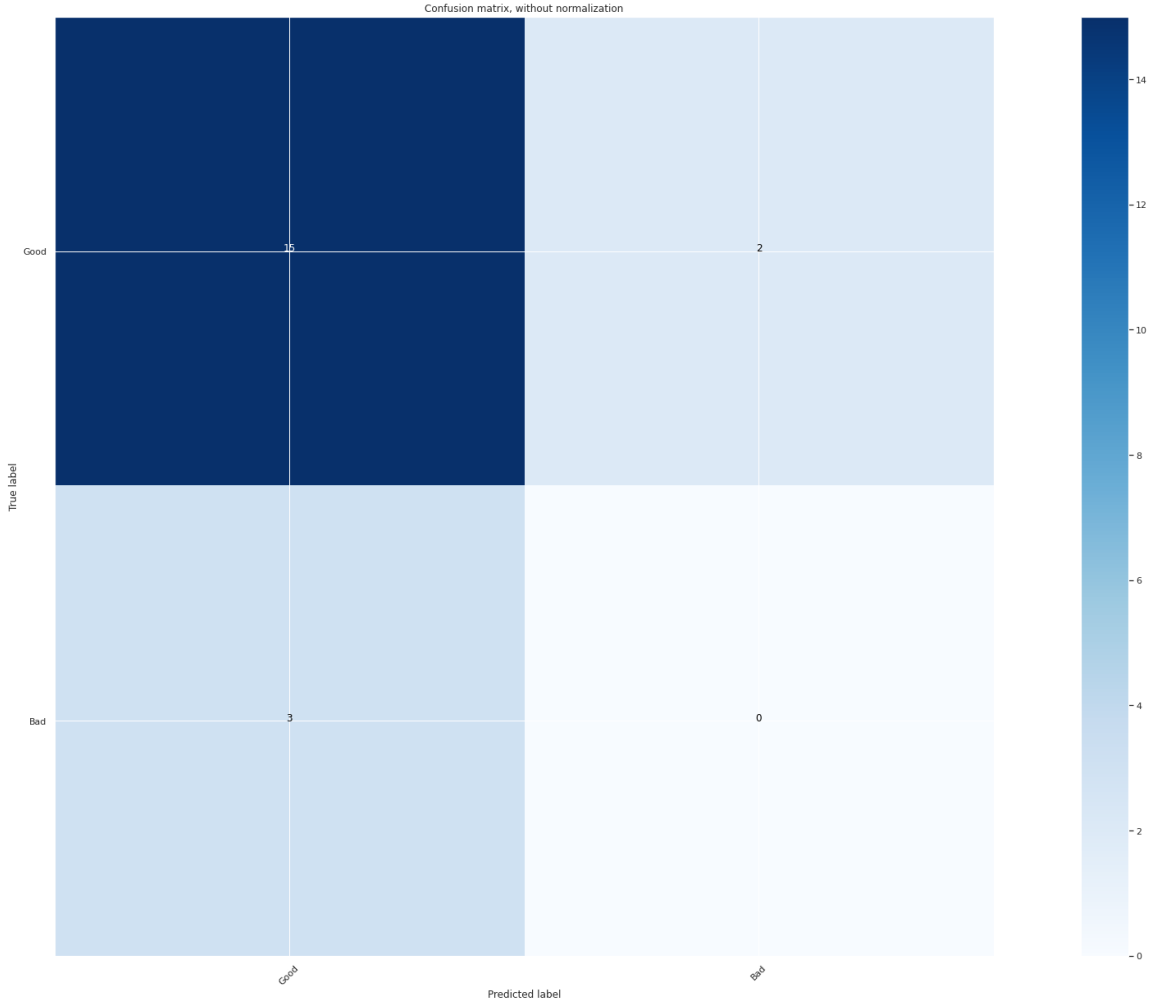
In [147]:

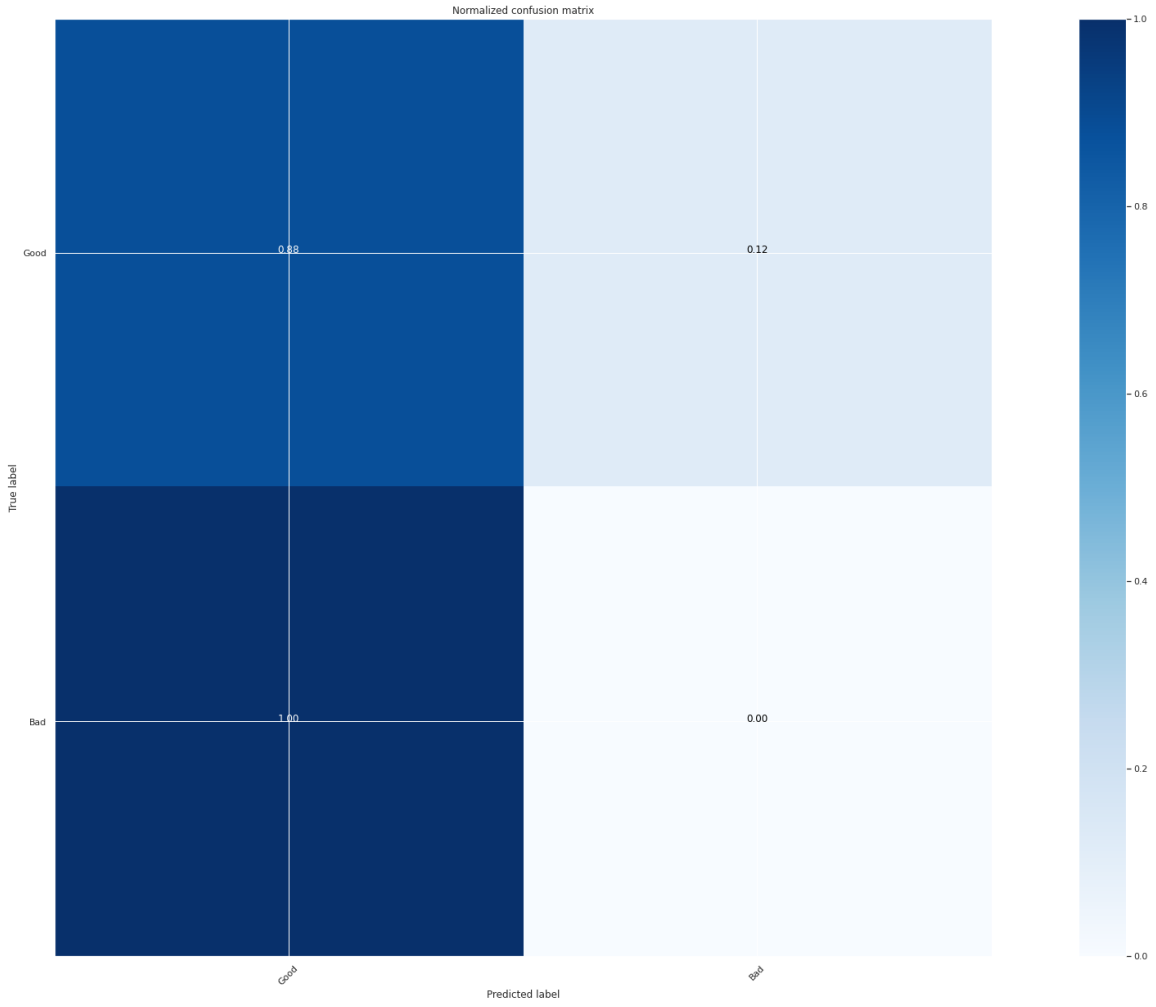
```
def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    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.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
```

In [148]:

```
#Compute confusion matrix
from sklearn.metrics import confusion_matrix

class_names=["Good", "Bad"]
cnf_matrix = confusion_matrix(y_real, results)
np.set_printoptions(precision=2)

# Plot non-normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names,
                      title='Confusion matrix, without normalization')

# Plot normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names, normalize=True,
                      title='Normalized confusion matrix')

plt.show()
```

```
Confusion matrix, without normalization
[[15  2]
 [ 3  0]]
Normalized confusion matrix
[[0.88 0.12]
 [1.   0.  ]]
```




Normalized confusion matrix
Good
Bad
True label
0.88
0.12
1.00
0.00
Good
Bad
Predicted label
1.0
0.8
0.6
0.4
0.2
0.0