Mini-Project 1 - Joël Seytre

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1 Simple classification

First we import the necessary packages and generate our datasets

```
In [3]: from mp1 import *
        from keras.models import Sequential, clone_model
        from keras.layers import Dense, Activation, Conv2D, Flatten, Dropout, MaxPooling2D
        from keras.utils import to_categorical
        from keras.regularizers import l2, l1
```

```
In [4]: [X_train1, Y_train1] = generate_dataset_classification(300, 20)
        Y_train1 = to_categorical(Y_train1)
```

1.1 First neural network (simple)

We then load our neural network: simple linear classifier with 3 neurons, using softmax for output, cross-entropy as loss and printing accuracy as gradient descent occurs.

```
In [5]: model1 = Sequential()
        model1.add(Dense(3, input_shape=(5184,), activation='softmax'))
        model1.compile(optimizer='sgd', loss='categorical_crossentropy',
                      metrics=['accuracy'])
```

```
In [6]: model1.fit(X_train1[0:200], Y_train1[0:200],
                  validation_data=(X_train1[200:300], Y_train1[200:300]),
                  epochs=20, batch_size=32)
```

```
Train on 200 samples, validate on 100 samples
Epoch 1/20
200/200 [==============================] - 0s 2ms/step - loss: 8.4545 - acc: 0.2350
- val_loss: 9.6709 - val_acc: 0.4000
...
Epoch 20/20
200/200 [==============================] - 0s 100us/step - loss: 10.2350 - acc: 0.3650
- val_loss: 9.6709 - val_acc: 0.4000
```

```
Out[6]: <keras.callbacks.History at 0x1a461c49c18>
```

Instead of having to optimize the different settings of the Stochastic Gradient Descent, switching to Adam ensures good convergence.

```
In [7]: model1 = Sequential()
        model1.add(Dense(3, input_shape=(5184,), activation='softmax'))
        model1.compile(optimizer='adam', loss='categorical_crossentropy',
                     metrics=['accuracy'])
```

```
In [8]: model1.fit(X_train1[0:200], Y_train1[0:200],
                   validation_data=(X_train1[200:300], Y_train1[200:300]),
                   epochs=20, batch_size=32)
```

```
Train on 200 samples, validate on 100 samples
Epoch 1/20
200/200 [==============================] - 1s 3ms/step - loss: 2.0602 - acc: 0.3900
- val_loss: 2.5713 - val_acc: 0.5400
...
Epoch 20/20
200/200 [==============================] - 0s 105us/step - loss: 0.1272 - acc: 0.9950
- val_loss: 0.1271 - val_acc: 0.9900
```

```
Out[8]: <keras.callbacks.History at 0x1a462218ba8>
```

1.2 Checking the classifier

We can check our classifier for all 3 classes

```
In [9]: X_test_r = generate_a_rectangle()
        X_test_d = generate_a_disk()
        X_test_t = generate_a_triangle()[0]
        X_test_r = X_test_r.reshape(1, X_test_r.shape[0])
        X_test_d = X_test_d.reshape(1, X_test_d.shape[0])
        X_test_t = X_test_t.reshape(1, X_test_t.shape[0])
        print(model1.predict(X_test_r))
        print(model1.predict(X_test_d))
        print(model1.predict(X_test_t))
```

```
[[1. 0. 0.]]
[[0. 1. 0.]]
[[0. 0. 1.]]
```

1.3 We then extract the weights and visualize them

We can even recognize the different shapes.

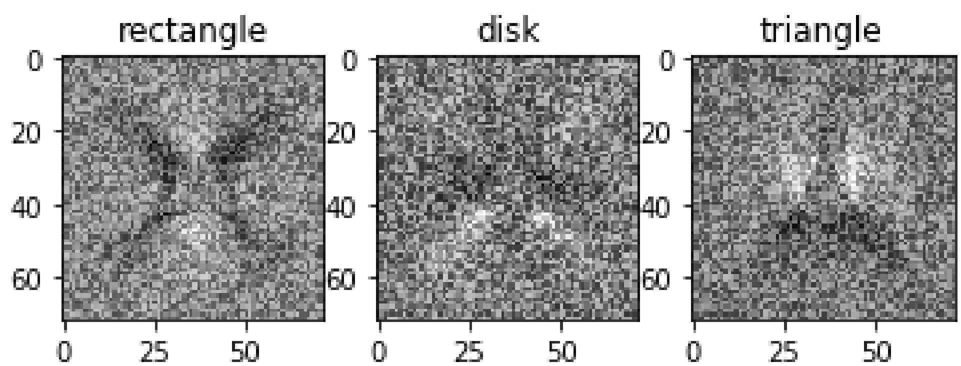
In [10]:
```
weights = model1.get_weights()[0].reshape(72,72,3)

plt.subplot(131)
plt.imshow(weights[:,:,0], cmap='gray')
plt.title('rectangle')

plt.subplot(132)
plt.imshow(weights[:,:,1], cmap='gray')
plt.title('disk')

plt.subplot(133)
plt.imshow(weights[:,:,2], cmap='gray')
plt.title('triangle')

plt.show()
```



2 A more complicated classification problem

First we generate the data and reshape it for the needs of the convolutional neural network (CNN). In order to have better results we use training and testing datasets that contain 1,000 images. Our CNN reaches a performance of: - 100% training accuracy - 93% testing at testing accuracy - 0.3 loss*

Note: implementing early stopping would have lowered the final *loss* at testing reached but seemingly not improved *accuracy*.

```
In [11]: n_samples = 1000

         [X_train2, Y_train2] = generate_dataset_classification(n_samples, 20, True)
         [X_test2, Y_test2] = generate_test_set_classification(n_samples, True)
         Y_train2 = to_categorical(Y_train2)
         X_train2 = X_train2.reshape(n_samples,72,72,1)
         X_test2 = X_test2.reshape(n_samples,72,72,1)
```

2.1 Trying out the previous model for this more complicated task

Spoilers: it doesn't work (because of changing shapes and positions)

```
In [12]: X_train_temp = X_train2.reshape(n_samples, 5184)
         X_test_temp = X_test2.reshape(n_samples, 5184)

         model1.fit(X_train_temp, Y_train2,
                   validation_data=(X_test_temp, Y_test2),
                   epochs=20, batch_size=32)
```

```
Train on 1000 samples, validate on 1000 samples
Epoch 1/20
1000/1000 [==============================] - 0s 108us/step - loss: 1.8027 - acc: 0.3640
- val_loss: 1.4765 - val_acc: 0.4790
...
Epoch 20/20
1000/1000 [==============================] - 0s 114us/step - loss: 0.9285 - acc: 0.6110
- val_loss: 1.0331 - val_acc: 0.5430
```

```
Out[12]: <keras.callbacks.History at 0x1a46ae25c18>
```

2.2 The final CNN used

64 filters of size 3x3 with 4x4 MaxPooling, 0.5 Dropout and a fully-connected 124-neuron hidden layer. Loss: cross-entropy; optimizer: adam.

```
In [13]: model2 = Sequential()
         model2.add(Conv2D(filters=64, kernel_size=(3,3), input_shape=(72,72,1), activation='rel
         model2.add(MaxPooling2D((4,4)))
         model2.add(Dropout(0.5))
         model2.add(Flatten())
         model2.add(Dense(124, activation='relu'))
         model2.add(Dense(3, activation='softmax'))
         model2.compile(optimizer='adam', loss='categorical_crossentropy',
                        metrics=['accuracy'])
         print(model2.summary())
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 70, 70, 64)        640
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 17, 17, 64)        0
_________________________________________________________________
dropout_1 (Dropout)          (None, 17, 17, 64)        0
_________________________________________________________________
flatten_1 (Flatten)          (None, 18496)             0
_________________________________________________________________
dense_3 (Dense)              (None, 124)               2293628
_________________________________________________________________
dense_4 (Dense)              (None, 3)                 375
=================================================================
Total params: 2,294,643
Trainable params: 2,294,643
Non-trainable params: 0
_________________________________________________________________
None
```

```
In [14]: model2.fit(X_train2, Y_train2,
                    validation_data=(X_test2, Y_test2),
                    epochs=50, batch_size=32)
```

```
Train on 1000 samples, validate on 1000 samples
Epoch 1/50
1000/1000 [==============================] - 9s 9ms/step - loss: 1.0912 - acc: 0.5030 - val_loss
Epoch 2/50
1000/1000 [==============================] - 6s 6ms/step - loss: 0.7679 - acc: 0.6990 - val_loss
...
Epoch 49/50
1000/1000 [==============================] - 6s 6ms/step - loss: 0.0093 - acc: 0.9980 - val_loss
Epoch 50/50
1000/1000 [==============================] - 6s 6ms/step - loss: 0.0064 - acc: 1.0000 - val_loss
```

```
Out[14]: <keras.callbacks.History at 0x1a46ae25278>
```

```
In [15]: model2.evaluate(X_test2, Y_test2)
```

```
1000/1000 [==============================] - 1s 994us/step
```

```
Out[15]: [0.27490175648313014, 0.925]
```

3 Regression problem

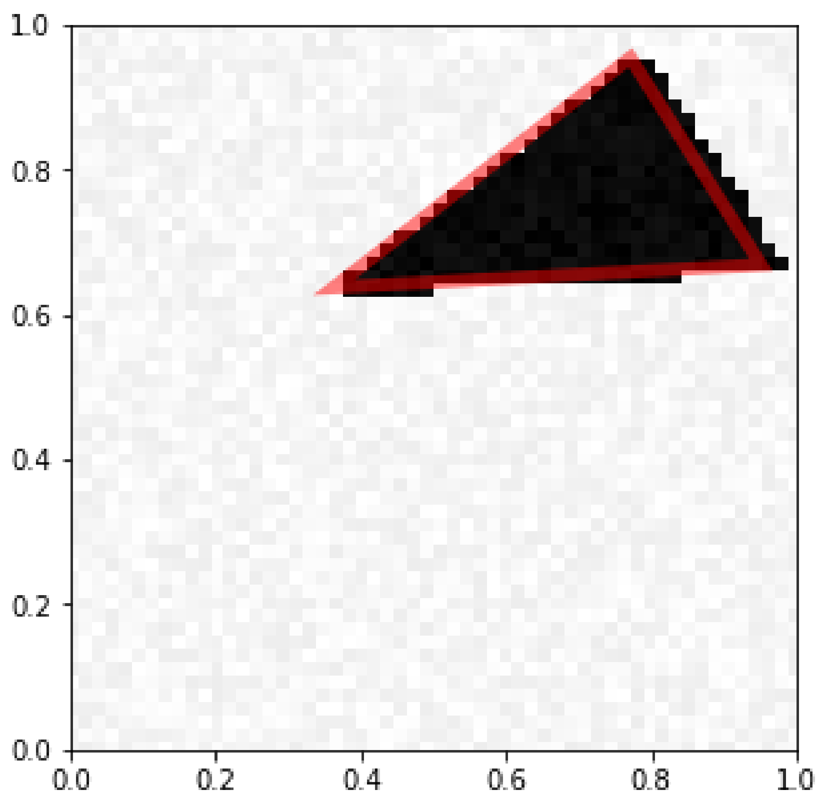
For this regression problem, we had to sort the vertices dataset in a way that we are going to describe. In the end we noticed that the task the CNN is trying to accomplish can necessitate different filters based on what vertex it wants to locate. To that end we ended up training a different CNN (that remains pretty simple in terms of architecture) for each of the 6 coordinates.

Note: we could have tried training only 3 different CNNs and seen if the same CNN can serve for x and y coordinates.

First we load the dataset and visualize an example.

In [16]:
```
[X_train3, Y_train3] = generate_dataset_regression(300, 20)
[X_test3, Y_test3] = generate_test_set_regression()
X_train3 = X_train3.reshape(300,72,72,1)
X_test3 = X_test3.reshape(300,72,72,1)

i=2
visualize_prediction(X_train3[i], Y_train3[i])
```



3.1 Normalizing the dataset

We can notice that the vertices are not sorted in the dataset at hand. Here we implement a function that sorts the vertices by computing the projection of the vertices on the (1,1) vector. We also substract 0.5 to the values so that the values are centered on zero (better initialization for the network).

Additionally, the function returns only one of the coordinates so that we can treat them all separately.

```
In [17]: def sort_vertices(dataset, index):
             middle = 0.5
         #     res = np.zeros((dataset.shape))
             res = np.zeros((300, 1))
             for i in range(0, 300):
                 temp1 = [dataset[i,2*m]+dataset[i,2*m+1] for m in range(0, 3)]
                 j = np.argmax(temp1)
                 k = np.argmin(temp1)
                 l = 3 - j - k
                 temp2 = [dataset[i,2*j]-middle, dataset[i,2*j+1]-middle,
                         dataset[i,2*k]-middle, dataset[i,2*k+1]-middle,
                         dataset[i,2*l]-middle, dataset[i,2*l+1]-middle]
                 res[i,:] = [temp2[index]]
             return res
```

```
In [18]: Y_train4 = [sort_vertices(Y_train3, i) for i in range(0, 6)]
         Y_test4 = [sort_vertices(Y_test3, i) for i in range(0, 6)]
```

3.2 CNN architecture

The model used is the same for all coordinates: 32 filters of size 9x9, on top of which we add a 32-neuron fully-connected layer. Activation: ReLu; loss: mean squared error; optimizer: Adam.

```
In [129]: reg_param = 0.00001

          model3 = Sequential()
          model3.add(Conv2D(filters=32, kernel_size=(5,5), input_shape=(72,72,1), activation='re
          model3.add(Conv2D(filters=32, kernel_size=(3,3), activation='relu', kernel_regularizer
          # model3.add(Conv2D(filters=32, kernel_size=(2,2), activation='relu', kernel_regulariz
          model3.add(Flatten())
          model3.add(Dense(64, activation='relu', kernel_regularizer=l2(reg_param)))
          model3.add(Dense(1))
          # model3.add(Dense(6))
          model3.compile(optimizer='adam', loss='mean_squared_error')
          print(model3.summary())
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_82 (Conv2D)           (None, 68, 68, 32)        832
_________________________________________________________________
conv2d_83 (Conv2D)           (None, 66, 66, 32)        9248
_________________________________________________________________
flatten_40 (Flatten)         (None, 139392)            0
_________________________________________________________________
dense_77 (Dense)             (None, 64)                8921152
_________________________________________________________________
dense_78 (Dense)             (None, 1)                 65
=================================================================
Total params: 8,931,297
Trainable params: 8,931,297
Non-trainable params: 0
_________________________________________________________________
None
```

3.3 Training our 6 CNNs

Here we train our 6 CNNs one after the other. Given the highly non-convex loss function, several runs are necessary to obtain a good performance for each coordinate.

For that reason we retrain the models whose performance is not deemed good enough (criteria: validation loss > 0.05).

```
In [135]: threshold = 0.05
          retrain_from_scratch = False
          errors = np.ones((6,2))
          for i in range(0, 6):
              try:
                  train_error = models[i].evaluate(X_train3, Y_train4[i], verbose = 0)
                  test_error = models[i].evaluate(X_test3, Y_test4[i], verbose = 0)
                  print("Evaluating model %i: train error %.3f - test error %.3f" % (i, train_er
              except:
                  try:
                      print("\nModel %i/%i was not defined..." % (i, len(models)))
                  except:
                      print("\nModels not defined!")
                      models = [clone_model(model3) for _ in range(0, 6)]
                  test_error = 1
              if test_error > threshold:
                  print("\n\nRetraining model %i because it was above threshold (%.3f vs %.3f)"
                  if retrain_from_scratch:
                      models[i] = clone_model(model3)
                      models[i].compile(optimizer='adam', loss='mean_squared_error')
                  models[i].fit(X_train3, Y_train4[i], validation_data=(X_test3, Y_test4[i]), ep
                  print("\n\n")
                  train_error = models[i].evaluate(X_train3, Y_train4[i], verbose = 0)
                  test_error = models[i].evaluate(X_test3, Y_test4[i], verbose = 0)
                  print("Evaluating model %i: train error %.3f - test error %.3f" % (i, train_er
              errors[i,:] = [train_error, test_error]
          print("\nDone evaluating models!")
```

```
Evaluating model 0: train error 0.009 - test error 0.030
Evaluating model 1: train error 0.007 - test error 0.028
Evaluating model 2: train error 0.014 - test error 0.037
Evaluating model 3: train error 0.012 - test error 0.036
Evaluating model 4: train error 0.003 - test error 0.047
Evaluating model 5: train error 0.003 - test error 0.050

Done evaluating models!
```

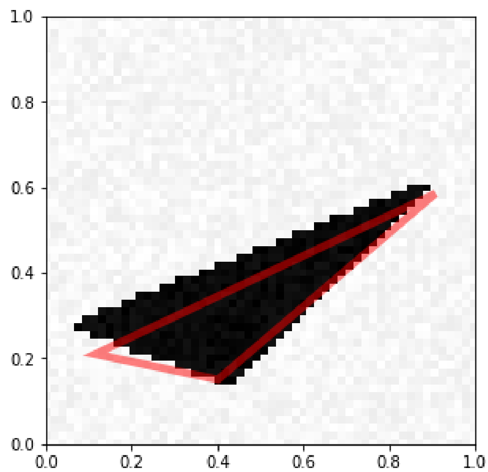
3.4 Visualization of the results

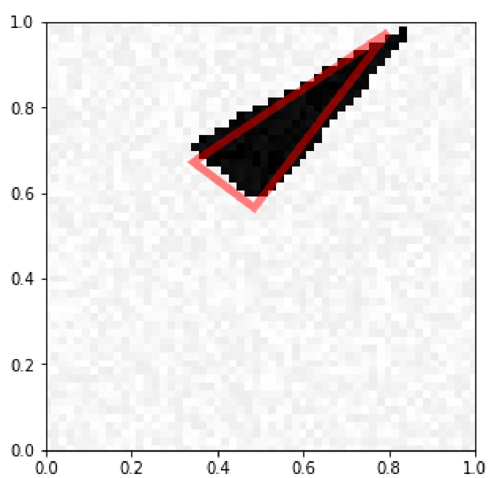
The results are decent. There is quite a bit of overfitting: I experimented with L1, L2 regularization as well as dropout. With this setup I manage to get under 0.05 validation loss on all coordinates.

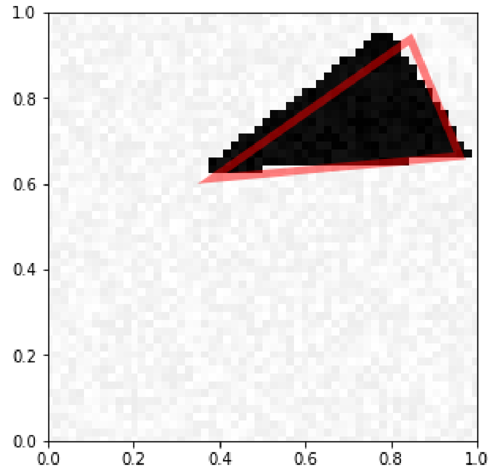
I believe they could be improved by maybe figuring out a better architecture (how can we regularize?) and by expanding the dataset.

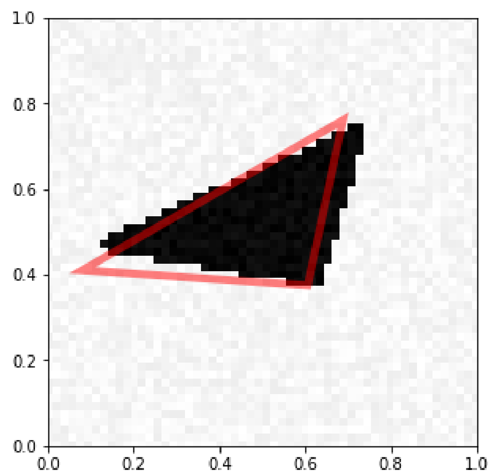
3.4.1 Visualization of training results

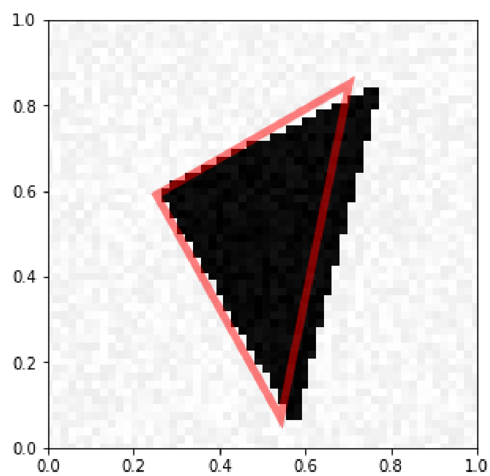
```
In [136]: for i in range(0,5):
              predictions = np.array([models[k].predict(X_train3)[i,0]+0.5 for k in range(0,6)])
              visualize_prediction(X_train3[i,:,:], predictions)
```





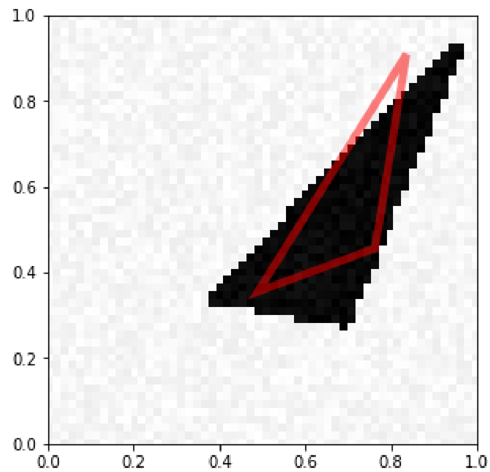


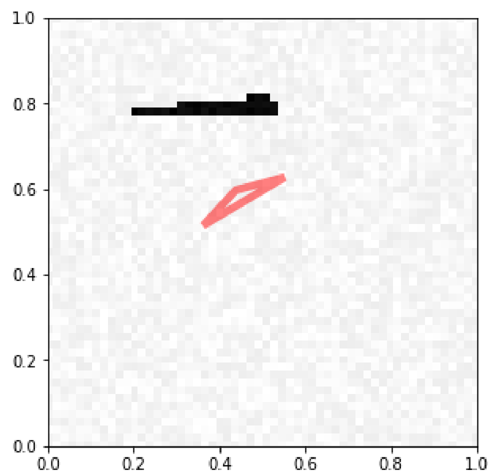


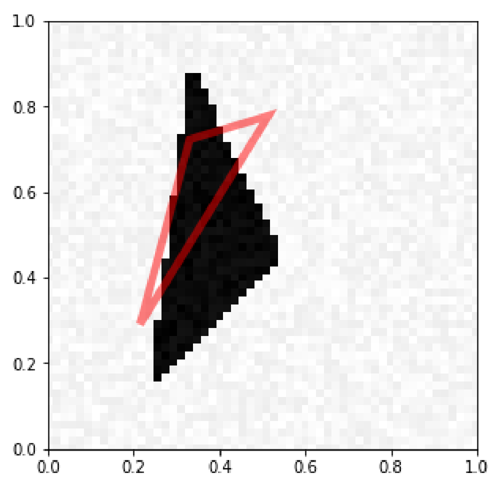


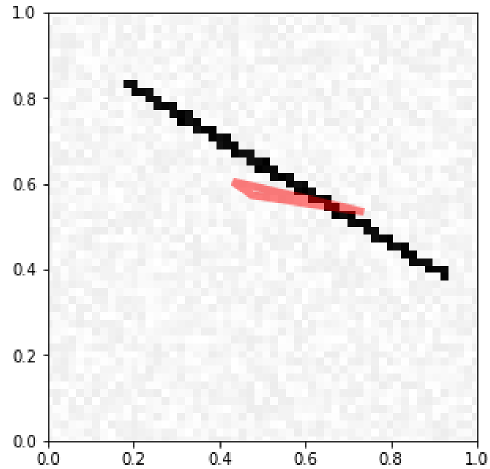
3.4.2 Visualization of testing results

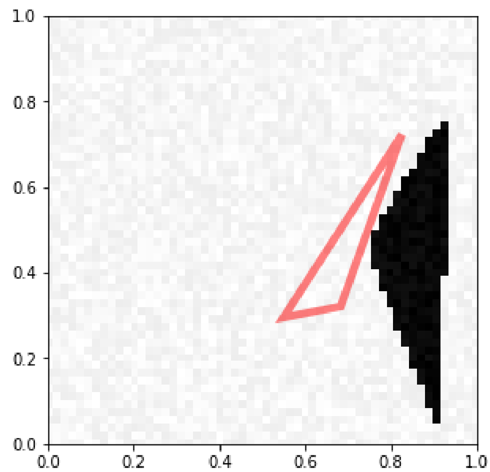
```
In [137]: for i in range(0,5):
              predictions = np.array([models[k].predict(X_test3)[i,0]+0.5 for k in range(0,6)])
              visualize_prediction(X_test3[i,:,:], predictions)
```








1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0


1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0