ResNet50

Residual learning framework ResNet is a powerful backbone model that is used very frequently in many computer vision tasks. On the ImageNet dataset residual nets with a depth of up to 152 layers---8x deeper than VGG nets but still having lower complexity.

AlexNet, the winner of ImageNet 2012 and the model that apparently kick started the focus on deep learning had only 8 convolutional layers, the VGG network had 19 and Inception or GoogleNet had 22 layers and ResNet 152 had 152 layers. ResNet-50 that is a smaller version of ResNet 152 and frequently used for transfer learning. ResNet uses skip connection to add the output from an earlier layer to a later layer. This helps it mitigate the vanishing gradient problem

```
In [1]: #!pip install keras==2.1.2
In [2]: import tensorflow as tf
    tf.test.gpu_device_name()
Out[2]: ''
```

Data preparation

```
In [3]: from glob import glob
from sklearn.model_selection import train_test_split

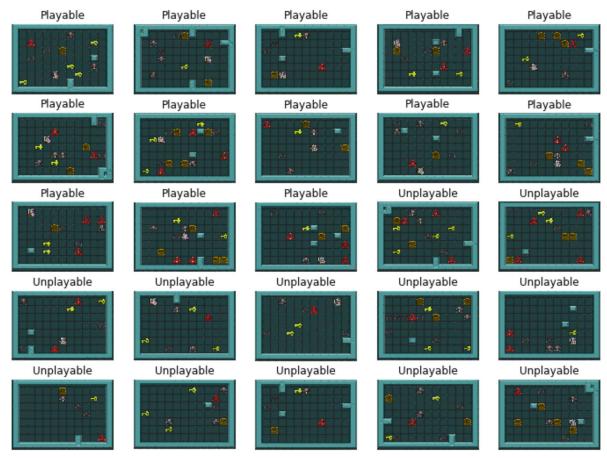
Playable = glob('train/zeldaPlayablelevels/*.jpg')
Unplayable = glob('train/zeldaUnplayablelevels/*.jpg')

Playable_train, Playable_test = train_test_split(Playable, test_size=0.30)
Unplayable_train, Unplayable_test = train_test_split(Unplayable, test_size=0.30)

TRAIN_DIR = 'train'
TEST_DIR = 'trest'
```

Plot some random images from the dataset.

```
In [4]:
        import numpy as np
        from PIL import Image
        import matplotlib.pyplot as plt
        Playable = np.random.choice(Playable_train, 13)
        Unplayable = np.random.choice(Unplayable_train, 12)
        data = np.concatenate((Playable, Unplayable))
        labels = 13 * ['Playable'] + 12 *['Unplayable']
        N, R, C = 25, 5, 5
        plt.figure(figsize=(12, 9))
        for k, (src, label) in enumerate(zip(data, labels)):
            im = Image.open(src).convert('RGB')
            plt.subplot(R, C, k+1)
            plt.title(label)
            plt.imshow(np.asarray(im))
            plt.axis('off')
```



Model customization

```
In [5]: from keras.models import Model
        from keras.layers import Dense, GlobalAveragePooling2D, Dropout
        #from keras.applications.inception v3 import InceptionV3, preprocess input
        from keras.applications.resnet50 import ResNet50, preprocess input
        CLASSES = 2
        HEIGHT = 300
        WIDTH = 300
        base_model = ResNet50(weights='imagenet',
                               include_top=False,
                               input_shape=(HEIGHT, WIDTH, 3))
        x = base_model.output
        x = GlobalAveragePooling2D(name='avg_pool')(x)
        x = Dropout(0.4)(x)
        predictions = Dense(CLASSES, activation='softmax')(x)
        model = Model(inputs=base_model.input, outputs=predictions)
        # transfer learning
        for layer in base model.layers:
            layer.trainable = False
        model.compile(optimizer='adam',
                      loss='categorical crossentropy',
                      metrics=['accuracy'])
```

Using TensorFlow backend.

/Users/friends/anaconda3/envs/udacity-ehr-env/lib/python3.7/site-packages/ker as_applications/resnet50.py:265: UserWarning: The output shape of `ResNet50(i nclude_top=False)` has been changed since Keras 2.2.0.

warnings.warn('The output shape of `ResNet50(include top=False)` '

Data augmentation

```
In [6]: | from keras.preprocessing.image import ImageDataGenerator
        WIDTH = 300
        HEIGHT = 300
        BATCH_SIZE = 32
        # data prep
        train datagen = ImageDataGenerator(
            preprocessing_function=preprocess_input,
            rotation_range=40,
            width_shift_range=0.2,
            height_shift_range=0.2,
            shear_range=0.2,
            zoom_range=0.2,
            horizontal flip=True,
            fill_mode='nearest')
        validation_datagen = ImageDataGenerator(
            preprocessing_function=preprocess_input,
            rotation_range=40,
            width_shift_range=0.2,
            height shift range=0.2,
            shear range=0.2,
            zoom range=0.2,
            horizontal_flip=True,
            fill mode='nearest')
        train generator = train datagen.flow from directory(
            TRAIN DIR,
            target size=(HEIGHT, WIDTH),
                 batch_size=BATCH_SIZE,
                 class mode='categorical')
        validation generator = validation datagen.flow from directory(
            TEST DIR,
            target_size=(HEIGHT, WIDTH),
            batch_size=BATCH_SIZE,
            class_mode='categorical')
```

Found 2018 images belonging to 2 classes. Found 30 images belonging to 2 classes.

Plot some images result of data augmentation.

```
In [7]: x_batch, y_batch = next(train_generator)

plt.figure(figsize=(12, 9))
for k, (img, lbl) in enumerate(zip(x_batch, y_batch)):
    plt.subplot(4, 8, k+1)
    plt.imshow((img + 1) / 2)
    plt.axis('off')
```

```
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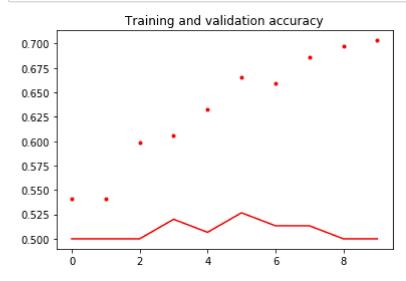
loats or [0..255] for integers).

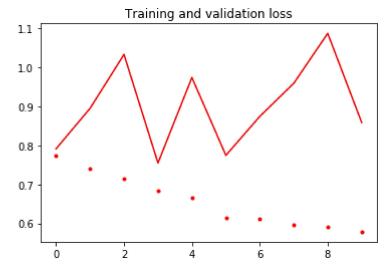
Clipping input data to the valid range for imshow with RGB data ([0..1] for f loats or [0..255] for integers).

Transfer learning

```
Epoch 1/10
20/20 [========================= ] - 995s 50s/step - loss: 0.7740 - accur
acy: 0.5406 - val_loss: 0.7914 - val_accuracy: 0.5000
Epoch 2/10
20/20 [=========================] - 965s 48s/step - loss: 0.7406 - accur
acy: 0.5406 - val loss: 0.8948 - val accuracy: 0.5000
Epoch 3/10
20/20 [========================= ] - 933s 47s/step - loss: 0.7067 - accur
acy: 0.5984 - val loss: 1.0331 - val accuracy: 0.5000
20/20 [================ ] - 966s 48s/step - loss: 0.6842 - accur
acy: 0.6062 - val loss: 0.7548 - val accuracy: 0.5200
Epoch 5/10
20/20 [========================= ] - 963s 48s/step - loss: 0.6658 - accur
acy: 0.6328 - val_loss: 0.9739 - val_accuracy: 0.5067
Epoch 6/10
20/20 [======================== ] - 927s 46s/step - loss: 0.6098 - accur
acy: 0.6656 - val loss: 0.7744 - val accuracy: 0.5267
Epoch 7/10
20/20 [======================== ] - 963s 48s/step - loss: 0.6112 - accur
acy: 0.6594 - val_loss: 0.8742 - val_accuracy: 0.5133
Epoch 8/10
20/20 [========================= ] - 962s 48s/step - loss: 0.5973 - accur
acy: 0.6859 - val loss: 0.9592 - val accuracy: 0.5133
Epoch 9/10
20/20 [=============== ] - 965s 48s/step - loss: 0.5911 - accur
acy: 0.6969 - val_loss: 1.0871 - val_accuracy: 0.5000
Epoch 10/10
20/20 [=========================] - 1040s 52s/step - loss: 0.6017 - accu
racy: 0.7033 - val_loss: 0.8587 - val_accuracy: 0.5000
```

```
In [9]:
        def plot_training(history):
          acc = history.history['accuracy']
          val_acc = history.history['val_accuracy']
           loss = history.history['loss']
          val_loss = history.history['val_loss']
           epochs = range(len(acc))
          plt.plot(epochs, acc, 'r.')
           plt.plot(epochs, val_acc, 'r')
          plt.title('Training and validation accuracy')
           plt.figure()
          plt.plot(epochs, loss, 'r.')
           plt.plot(epochs, val_loss, 'r-')
           plt.title('Training and validation loss')
          plt.show()
        plot_training(history)
```



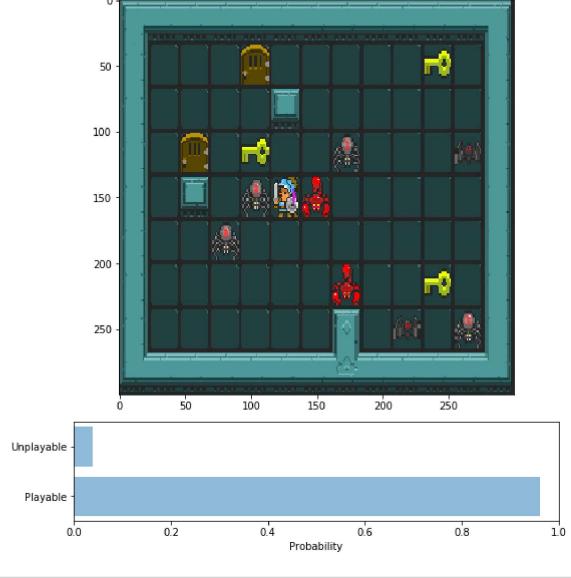


Prediction of the custom model

```
In [10]:
         import numpy as np
         import matplotlib.pyplot as plt
         import matplotlib.gridspec as gridspec
         from keras.preprocessing import image
         from keras.models import load_model
         def predict(model, img):
              """Run model prediction on image
             Args:
                 model: keras model
                 img: PIL format image
             Returns:
                  list of predicted labels and their probabilities
             x = image.img_to_array(img)
             x = np.expand_dims(x, axis=0)
             x = preprocess input(x)
             preds = model.predict(x)
             return preds[0]
         def plot preds(img, preds):
              """Displays image and the top-n predicted probabilities in a bar graph
                preds: list of predicted labels and their probabilities
             labels = ("Playable", "Unplayable")
             gs = gridspec.GridSpec(2, 1, height_ratios=[4, 1])
             plt.figure(figsize=(8,8))
             plt.subplot(gs[0])
             plt.imshow(np.asarray(img))
             plt.subplot(gs[1])
             plt.barh([0, 1], preds, alpha=0.5)
             plt.yticks([0, 1], labels)
             plt.xlabel('Probability')
             plt.xlim(0, 1)
             plt.tight layout()
```

```
In [11]: model = load_model(MODEL_FILE)
```

Out[12]: array([0.96094215, 0.03905782], dtype=float32)



```
In [13]: TEST_DIR = 'test'
    img_width = 300
    img_height = 300
```

Predict classes

```
In [14]: import numpy
    test_generator = ImageDataGenerator()
    test_data_generator = test_generator.flow_from_directory(
        TEST_DIR, # Put your path here
        target_size=(img_width, img_height),
        batch_size=32,
        shuffle=False)
    test_steps_per_epoch = numpy.math.ceil(test_data_generator.samples / test_data_generator.batch_size)
    predictions = model.predict_generator(test_data_generator, steps=test_steps_per_epoch)
    # Get most likely class
    predicted_classes = numpy.argmax(predictions, axis=1)
```

Found 30 images belonging to 2 classes.

Get ground-truth classes and class-labels

```
In [15]: true_classes = test_data_generator.classes
    class_labels = list(test_data_generator.class_indices.keys())
```

Use scikit-learn to get statistics

	precision	recall	f1-score	support
zeldaPlayablelevels	0.50	1.00	0.67	15
zeldaUnplayablelevels	0.00	0.00	0.00	15
accuracy			0.50	30
macro avg	0.25	0.50	0.33	30
weighted avg	0.25	0.50	0.33	30

/Users/friends/anaconda3/envs/udacity-ehr-env/lib/python3.7/site-packages/skl earn/metrics/_classification.py:1272: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

```
_warn_prf(average, modifier, msg_start, len(result))
```