CP-final-project-dmp131

April 29, 2019

This notebook requires the following Python packages which can be installed using `pip`:

- `keras`
- `opencv-python`
- `numpy`
- `matplotlib`
- `ipywidgets`

Enable interactive plots by running `jupyter nbextension enable --py widgetsnbextension`

There are interactive plots which can be generated by running the notebook. Lines which train the models have been commented out so the notebook should only take a couple minutes to run. If the interactive plots do not work, I have added some `.gifs` to illustrate the same figures.

For my final project I wanted to try to solve a niche problem that I have encountered in my experiences of competitive jump rope. There are two types of jump rope events that are done at competitions: freestyle and speed. Freestyle is certainly the more exciting of the two and involves performing as many difficult and diverse skills as possible in a certain time window as shown in the clip below:

```
In [13]: %%HTML
         <video width="640" height="360" controls>
           <source src="writeup_videos/summit_routine.mp4" type="video/mp4">
         </video>
```

```
<IPython.core.display.HTML object>
```

Speed involves trying to jump the rope as many times as possible in either 30 seconds or 3 minutes. Jumpers have adapted a jogging step motion to maximize speed as it minimizes the amount of time that your feet are off the ground. This has rapidly increased speed scores to the point that human judges became unable to count every single jump. The compromise has been to have four judges count only the right foot of the jumper and then average the doubled count from each judge. Athletes have continued to increase in speed however, and even this one-foot counting is becoming impossible for human judges as can be seen in the video below of a previous world record in the 30 second event (note the score of 108 is right foot only and the final score is actually 216, try to count yourself, it's pretty difficult even for an experienced jumper!):

In [14]:
```
%%HTML
<video width="640" height="360" controls>
  <source src="writeup_videos/cen_30s.mp4" type="video/mp4">
</video>
```

```
<IPython.core.display.HTML object>
```

This leads to the question of can an algorithm out-perform human judges in counting speed from video? I will attempt to build a neural network approach to solve this problem.

Thankfully I have been involved in this sport for over a decade and I have a collection of videos of speed jumping that I can play in slow motion and count each jump (note: I will be training this model to count *both* feet) to label the data which will be fed into the neural network.

I wrote the `label_videos.py` script to create the dataset that will be used to train the model. It reads any video files in the `unlabeled_videos/` directory and plays them at 10fps listening for an `s` key tap on each jump. It will save a `numpy` array containing the frame numbers of each jump.

I labeled 15 videos for a total of 14,415 frames.

The first decision we have to make is to decide how to represent the problem. I opted to represent the problem as a multi-class classification problem where each speed video is split into a k-frame window and the output of the neural network is a vector of values between 0 and 1 indicating whether a jump occured at that particular frame.

Let's take a look at what this looks like by using a window of 4 frames. I will continue using a window of 4 frames for reason that will become clear later:

In [15]:
```python
import os

data_dir = os.getcwd() + '/data/'
video_dir = 'speed_videos/'
annotation_dir = 'speed_annotations/'

frame_size = 128
window_size = 4
use_flow_field = False
grayscale = True
```

In [16]:
```python
import cv2
import numpy as np

def open_video(file, window_size, flow_field=False):
    cap = cv2.VideoCapture(file)
    frameCount = int(cap.get(cv2.CAP_PROP_FRAME_COUNT))
    frameWidth = frame_size
    frameHeight = frame_size

    if grayscale:
        buf = np.zeros((frameCount, frameHeight, frameWidth), dtype=np.uint8)
    else:
        buf = np.zeros((frameCount, frameHeight, frameWidth, 3))
```

```
        fc = 0
        ret = 1

        while True:
            try:
                ret, img = cap.read()
                if grayscale:
                    img = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
                else:
                    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
                img = cv2.resize(img, (frame_size, frame_size), interpolation=cv2.INTER_AI
                buf[fc] = img.copy()
                fc += 1
            except Exception as e:
                break
        cap.release()
        if grayscale:
            buf = np.reshape(buf, (frameCount, frameHeight, frameWidth, 1))
        return buf
```

```
In [111]: import ipywidgets as widgets
          from ipywidgets import interact, interact_manual
          from ipywidgets import interactive
          import matplotlib.pyplot as plt

          def plot_frame(clip, label, save_frames=False):
              def f(i):
                  fig = plt.figure(figsize=(10, 5))
                  ax = plt.subplot(121)
                  ax.set_xticks([])
                  ax.set_yticks([])
                  save_dir = ''
                  if use_flow_field:
                      flow = flow_to_rgb(clip[i, ...])
                      ax.imshow(flow)
                      save_dir = 'flow'
                  elif grayscale:
                      ax.imshow(clip[i, ..., 0], cmap='gray')
                      save_dir = 'grayscale'
                  else:
                      ax.imshow(clip[i, ..., 0], cmap='gray')
                      save_dir = 'rgb'

                  ax = plt.subplot(122)
                  ax.set_xticks([])
                  ax.set_yticks([])
                  ax.plot(np.arange(window_size), label)
                  ax.scatter(i, label[i], c='r')
```

```
            if save_frames:
                fig.savefig('conv_vis/' + save_dir + '/%d.png' % i)
            plt.show()
        return f
```

In [19]:
```
def flow_to_rgb(flow):
    mag, ang = cv2.cartToPolar(flow[..., 0], flow[..., 1])
    hsv = np.zeros((flow.shape[0], flow.shape[1], 3))
    hsv[..., 1] = 255
    hsv[..., 0] = ang * 180 / np.pi / 2
    hsv[..., 2] = cv2.normalize(mag, None, 0, 255, cv2.NORM_MINMAX)
    return cv2.cvtColor(np.uint8(hsv), cv2.COLOR_HSV2RGB)
```

In [20]:
```
video_path = 'hiro_2.mp4'

#get a single vector field from two frames of the video
def get_flow_field(video, i, j):
    prev = cv2.cvtColor(video[i], cv2.COLOR_BGR2GRAY)
    next = cv2.cvtColor(video[j], cv2.COLOR_BGR2GRAY)
    flow = cv2.calcOpticalFlowFarneback(prev, next, None, 0.5, 3, 15, 3, 5, 1.2, 0)
    return flow

# convert video to sequence of vector fields representing optical flow over time
def video_to_flow_field(video):
    flow = np.array([])
    for i in range(len(video) - 1):
        field = get_flow_field(video, i, i + 1)
        flow = np.append(flow, field)
    return np.reshape(flow, (video.shape[0] - 1, video.shape[1], video.shape[2], 2))


def get_clip_and_label(video_path):
    video = open_video(data_dir + video_dir + video_path, window_size=window_size)
    label_path = data_dir + annotation_dir + video_path.replace('.mp4', '.npy')
    label = np.load(label_path)
    start_frame = np.random.randint(0, len(video) - window_size)
    clip = video[start_frame:start_frame + window_size]
    if use_flow_field:
        flow_field = video_to_flow_field(np.uint8(clip))
        label_clip = label[np.where(label < start_frame + window_size - 1)]
        label_clip = label_clip[np.where(label_clip > start_frame)]
        y = np.zeros(window_size - 1)
    else:
        label_clip = label[np.where(label < start_frame + window_size)]
        label_clip = label_clip[np.where(label_clip > start_frame)]
    y = np.zeros(window_size)
    for frame in label_clip:
        y[frame - start_frame] = 1
```

```
        if use_flow_field:
            return flow_field, y
        else:
            return clip, y

clip, y = get_clip_and_label(video_path)
if use_flow_field:
    interactive_plot = interactive(plot_frame(clip, y), i=(0, window_size - 2))
else:
    interactive_plot = interactive(plot_frame(clip, y), i=(0, window_size - 1))
output = interactive_plot.children[-1]
output.layout.height = '360px'
interactive_plot
```

```
interactive(children=(IntSlider(value=1, description='i', max=3), Output(layout=Layout(height=
```

Move the slider in the figure above to view different frames of the 4 frame clip. The label has been converted to a one-hot representation where 1 corresponds to a jump on that particular frame and is shown in the plot on the right.

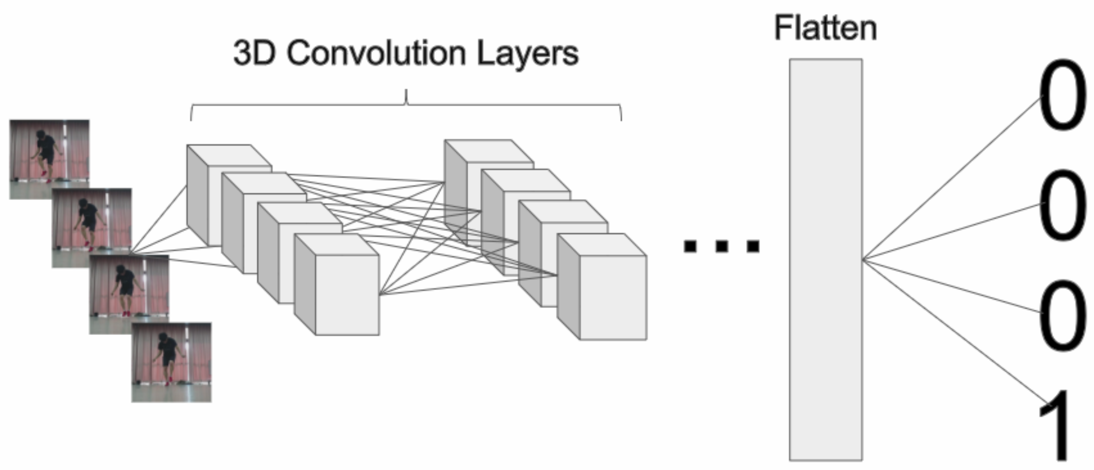
Now that we have a representation for the problem, we should try a few approaches to training our model on the data. The approaches that I will try involve training the model on the full RGB video frames, grayscale frames, and a motion vector field computed using the Lucas-Kanade optical flow algorithm (https://en.wikipedia.org/wiki/Lucas%E2%80%93Kanade_method)

The model will consist of stacked 3D convolutions where each kernel is convolved over both the spatial dimensions of the frames but also the time dimension of the video. The goal of this is to learn spatio-temporal features of jumps which will then be used to classify the frames as either containing a jump or not.

A summary of the model architecture is shown below. The video clip is fed into a sequence of 3D convolution layers and the final feature vector is flattened and mapped to the four binary output values. Not shown are pooling layers after each convolution layer

In [72]:
```
from IPython.display import Image
Image(filename='figures/model_architecture.png', width=438, height=203)
```

Out[72]:



The 3D convolution layers are identical to time distributed 2D convolutions. Here is an intuitive animation of what a 3D convolution looks like when applied to a 3D input such as a video where we consider the 3rd dimension of the data to be time (https://thomelane.github.io/convolutions/3DConv.html):

```
In [1]: %%HTML
        <img src="figures/3d_convolution.gif" width="438" height="203" />
```

```
<IPython.core.display.HTML object>
```

The reason that a 4 frame window was selected is so the problem can be framed as categorical classification. At world record level speed (currently 226 jumps in 30 seconds by Cen Xiaolin) jumpers complete ~7.5 jumps per second. Assuming that the videos we are using are 30fps, we can compute the maximum number of frames we can use and be certain that only one jump will occur in that window:

$$frames = \frac{1}{\frac{7.5jumps}{1second}\frac{1second}{30frames}} = 4$$

Meaning we should use a window size of 4 so that our one-hot labels only ever have a single `1`.

We will train the model using Keras' built-in `categorical_crossentropy` loss function which is defined as:

$$-\frac{1}{k}\sum_{i=1}^{k}\sum_{c=1}^{k} I_c(y_i)log\hat{y}_i$$

Where y_i is the label for the ith frame of the input clip, $\hat{y}_i$ is the model prediction for the ith frame of the input clip and $I_c(y_i) = 1$ if $y_i \in c$ and 0 otherwise

By normalizing our input values to be between 0 and 1 we can use a sigmoid activation function with categorical cross-entropy to perform stochastic gradient descent to train the model.

We will also measure the categorical accuracy of the model which is defined as:

$$\frac{1}{N}\sum_{\mathbf{y}} eq(argmax\ \mathbf{y}, argmax\ \hat{\mathbf{y}})$$

Where we have an observation matrix $\mathbf{Y}$

$$\mathbf{Y} = \{\mathbf{y_1}, ..., \mathbf{y_N}\} = \{\{y_{1_1}, ..., y_{1_k}\}, ..., \{y_{N_1}, ..., y_{N_k}\}\}$$

and an identical prediction matrix $\hat{\mathbf{Y}}$

Where $eq(argmax\ \mathbf{y}, argmax\ \hat{\mathbf{y}}) = 1$ if $argmax\ \mathbf{y}$ is equal to $argmax\ \hat{\mathbf{y}}$ and we take the sum over all observations i.e. on average how often do predictions have maximum in the same spot as the true values.

For the sake of easy testing of different model parameters, I have written a class wich contains all of the necessary functionality as well as some of the util functions above for opening videos and converting videos to flow fields:

In [22]:
```
import numpy as np
import cv2
import os
import matplotlib.pyplot as plt

from keras.models import Sequential, Model
from keras.layers import Dense, Activation, Conv2D, MaxPooling2D, Conv3D, MaxPooling3I
from keras.layers import SpatialDropout1D
from keras.optimizers import SGD, Adam


class SpeedCounter:
    # initialize all of the model parameters and data directories
    def __init__(self,
                 data_dir,
                 video_dir,
                 annotation_dir,
                 lr,
                 batch_size,
                 n_epochs,
                 n_filters=4,
                 kernel_size=3,
                 kernel_frames=4,
                 frame_size=128,
                 window_size=4,
                 use_flow_field=False,
                 grayscale=False,
                 verbose=False):
        self.data_dir = data_dir
        self.video_dir = video_dir
        self.annotation_dir = annotation_dir
        self.learning_rate = lr
```

```python
        self.batch_size = batch_size
        self.n_epochs = n_epochs
        self.n_filters = n_filters
        self.kernel_size = kernel_size
        self.kernel_frames = kernel_frames
        self.frame_size = frame_size
        self.window_size = window_size
        self.use_flow_field = use_flow_field
        self.grayscale = grayscale
        self.verbose = verbose

    # train the model using the expressed number of epochs
    def train(self):
        total_frames = self.get_total_frames() + 1
        print('Total Frames:', total_frames)
        print('Total Samples:', total_frames // self.window_size)

        model = self.stacked_model()

        sgd = SGD(lr=self.learning_rate, nesterov=True, decay=1e-6, momentum=0.9)

        model.compile(loss='categorical_crossentropy',
                      optimizer=sgd,
                      metrics=['categorical_accuracy'])

        print(model.summary())
        loss_graph = []
        accuracy_graph = []
        for epoch in range(self.n_epochs):
            print('Epoch %d / %d' % (epoch, self.n_epochs))
            epoch_loss = []
            epoch_accuracy = []
            for (x, y) in self.generate_batch():
                loss = model.train_on_batch(x, y)
                epoch_loss.append(loss[0])
                epoch_accuracy.append(loss[1])
                if self.verbose:
                    print('Loss: %.3f, Accuracy: %.3f' % (loss[0], loss[1]))
            loss_graph.append(np.mean(epoch_loss))
            accuracy_graph.append(np.mean(epoch_accuracy))
            print('Epoch Loss: %.3f, Epoch Accuracy: %.3f' % (loss_graph[-1], accurac



        # Save the weights
        if self.grayscale:
            name = 'grayscale'
        elif self.use_flow_field:
```

```
            name = 'flow'
        else:
            name = 'RGB'
        model.save_weights('models/model_weights%s.h5' % name)

        # Save the model architecture
        with open('models/model_architecture.json%s' % name, 'w') as f:
            f.write(model.to_json())

        plt.plot(loss_graph, label='loss')
        plt.title('model loss')
        plt.ylabel('loss')
        plt.xlabel('epoch')
        plt.legend(loc='best')
        plt.show()

        plt.plot(accuracy_graph, label='accuracy')
        plt.title('model accuracy')
        plt.ylabel('accuracy')
        plt.xlabel('epoch')
        plt.legend(loc='best')
        plt.show()

    # generate a batch of input target pairs using a generator function
    def generate_batch(self):
        x_batch = np.array([])
        y_batch = np.array([])
        for filename in os.listdir(self.data_dir + self.video_dir):
            video_path = self.data_dir + self.video_dir + filename
            label_path = self.data_dir + self.annotation_dir + filename.replace('.mp4
            label = np.load(label_path)
            video = self.open_video(video_path)
            num_clips = 0
            random_offset = np.random.randint(0, self.window_size)
            for start_frame in range(random_offset, len(video), self.window_size):
                if start_frame + self.window_size < len(video):
                    clip = video[start_frame:start_frame + self.window_size]
                    if self.use_flow_field:
                        flow_field = self.video_to_flow_field(np.uint8(clip))
                        label_clip = label[np.where(label < start_frame + self.window_
                        label_clip = label_clip[np.where(label_clip > start_frame)]
                        y = np.zeros(self.window_size - 1)
                    else:
                        label_clip = label[np.where(label < start_frame + self.window_
                        label_clip = label_clip[np.where(label_clip > start_frame)]
                        y = np.zeros(self.window_size)
                    for frame in label_clip:
                        y[frame - start_frame] = 1
```

```
                if self.use_flow_field:
                    x_batch = np.append(x_batch, flow_field)
                else:
                    x_batch = np.append(x_batch, clip / 255.)
                y_batch = np.append(y_batch, y)
                num_clips += 1
                if num_clips == self.batch_size:
                    num_clips = 0
                    if self.use_flow_field:
                        x_batch = np.reshape(x_batch, (-1, self.window_size - 1, s
                    elif self.grayscale:
                        x_batch = np.reshape(x_batch, (-1, self.window_size, self
                    else:
                        x_batch = np.reshape(x_batch, (-1, self.window_size, self
                    if self.use_flow_field:
                        y_batch = np.reshape(y_batch, (-1, self.window_size - 1))
                    else:
                        y_batch = np.reshape(y_batch, (-1, self.window_size))
                    yield {'video': x_batch}, {'frames': y_batch}
                    x_batch = np.array([])
                    y_batch = np.array([])

    # build uncompiled Keras model using 3D convolution layers
    def stacked_model(self):
        if self.use_flow_field:
            encoder = Input(shape=(self.window_size - 1, self.frame_size, self.frame_s
        elif self.grayscale:
            encoder = Input(shape=(self.window_size, self.frame_size, self.frame_size
        else:
            encoder = Input(shape=(self.window_size, self.frame_size, self.frame_size
        output = Conv3D(4, (2, 16, 16))(encoder)
        output = BatchNormalization()(output)
        output = Activation('relu')(output)
        output = MaxPooling3D((1, 2, 2))(output)
        output = Conv3D(8, (2, 8, 8))(output)
        output = BatchNormalization()(output)
        output = Activation('relu')(output)
        output = MaxPooling3D((1, 2, 2))(output)
        output = Conv3D(16, (1, 4, 4))(output)
        output = BatchNormalization()(output)
        output = Activation('relu')(output)
        output = MaxPooling3D((1, 2, 2))(output)
        output = Conv3D(32, (1, 3, 3))(output)
        output = BatchNormalization()(output)
        output = Activation('relu')(output)
        output = MaxPooling3D((1, 2, 2))(output)
        output = Conv3D(64, (1, 3, 3))(output)
        output = BatchNormalization()(output)
```

```
        output = Activation('relu')(output)
        output = MaxPooling3D((1, 2, 2))(output)
        output = Flatten()(output)
        if self.use_flow_field:
            output = Dense(self.window_size - 1, activation='softmax', name='frames')
        else:
            output = Dense(self.window_size, activation='softmax', name='frames')(outp
        model = Model(inputs=encoder,
                      outputs=output)
        return model

    # convert video to sequence of vector fields representing optical flow over time
    def video_to_flow_field(self, video):
        flow = np.array([])
        for i in range(len(video) - 1):
            field = self.get_flow_field(video, i, i + 1)
            flow = np.append(flow, field)
        return np.reshape(flow, (video.shape[0] - 1, video.shape[1], video.shape[2],

    #open a video as a 3D Numpy array
    def open_video(self, file):
        cap = cv2.VideoCapture(file)
        frameCount = int(cap.get(cv2.CAP_PROP_FRAME_COUNT))
        frameWidth = self.frame_size
        frameHeight = self.frame_size

        if self.grayscale:
            buf = np.zeros((frameCount, frameHeight, frameWidth), dtype=np.uint8)
        else:
            buf = np.zeros((frameCount, frameHeight, frameWidth, 3))

        fc = 0
        ret = 1

        while True:
            try:
                ret, img = cap.read()
                if self.grayscale:
                    img = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
                else:
                    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
                img = cv2.resize(img, (self.frame_size, self.frame_size), interpolatio
                buf[fc] = img.copy()
                fc += 1
            except Exception as e:
                break
        cap.release()
        if self.grayscale:
```

```
            buf = np.reshape(buf, (frameCount, frameHeight, frameWidth, 1))
        return buf

    #get a single vector field from two frames of the video
    def get_flow_field(self, video, i, j):
        prev = cv2.cvtColor(video[i], cv2.COLOR_BGR2GRAY)
        next = cv2.cvtColor(video[j], cv2.COLOR_BGR2GRAY)
        flow = cv2.calcOpticalFlowFarneback(prev, next, None, 0.5, 3, 15, 3, 5, 1.2, (
        return flow

    # get the total number of frames in the dataset
    def get_total_frames(self):
        total = 0
        for filename in os.listdir(self.data_dir + self.video_dir):
            label_path = self.data_dir + self.annotation_dir + filename.replace('.mp4
            label = np.load(label_path)
            total += label[-1]
        return total
```

Now we can create a SpeedCounter object and call the train function to train the model with the given parameters

```
In [10]: np.random.seed(42)  # set seed for reproducible research

         counter = SpeedCounter(data_dir=os.getcwd() + '/data/',
                                video_dir='speed_videos/',
                                annotation_dir='speed_annotations/',
                                lr=1e-3,
                                batch_size=32,
                                n_epochs=50,
                                frame_size=128,
                                window_size=4,
                                use_flow_field=False,
                                grayscale=True,
                                verbose=False)

         # uncomment to re-train model
         #counter.train()
```

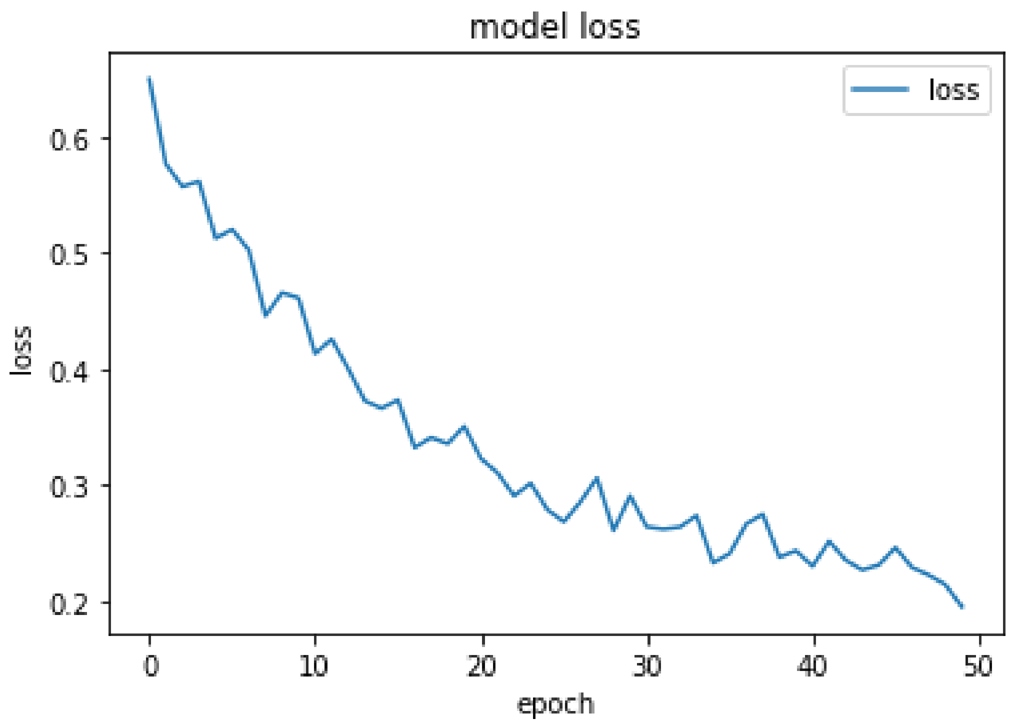
```
Total Frames: 14415
Total Samples: 3603
Model: "model_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
video (InputLayer)           (None, 4, 128, 128, 1)    0
_________________________________________________________________
conv3d_1 (Conv3D)            (None, 3, 113, 113, 4)    2052
```

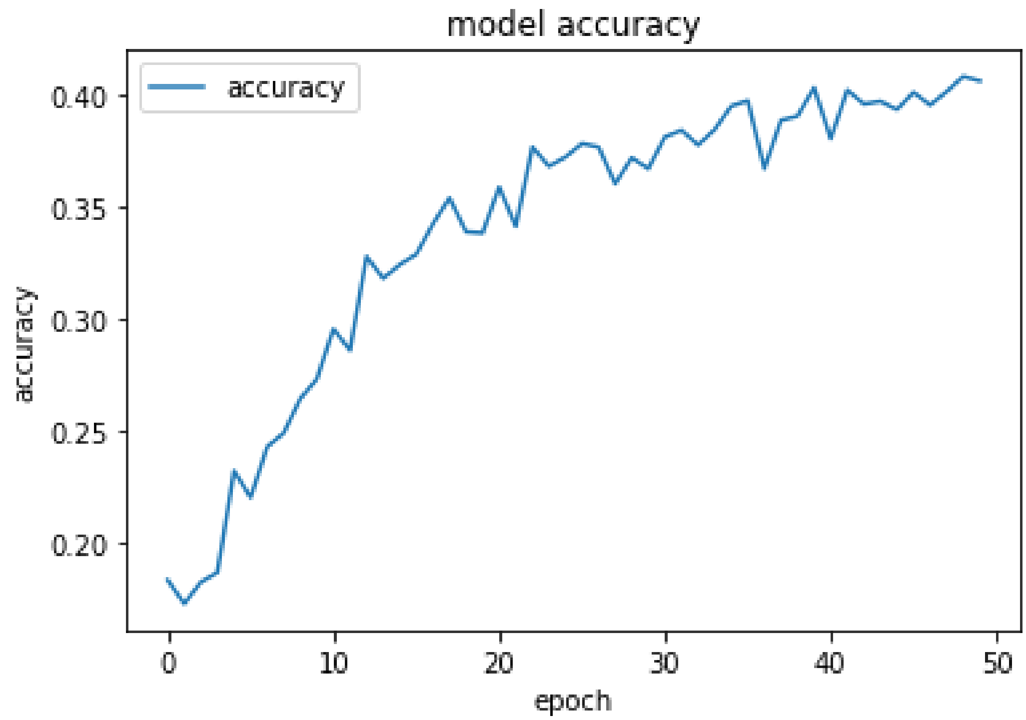
```
_________________________________________________________________
batch_normalization_1 (Batch (None, 3, 113, 113, 4)    16
_________________________________________________________________
activation_1 (Activation)    (None, 3, 113, 113, 4)    0
_________________________________________________________________
max_pooling3d_1 (MaxPooling3 (None, 3, 56, 56, 4)      0
_________________________________________________________________
conv3d_2 (Conv3D)            (None, 2, 49, 49, 8)      4104
_________________________________________________________________
batch_normalization_2 (Batch (None, 2, 49, 49, 8)      32
_________________________________________________________________
activation_2 (Activation)    (None, 2, 49, 49, 8)      0
_________________________________________________________________
max_pooling3d_2 (MaxPooling3 (None, 2, 24, 24, 8)      0
_________________________________________________________________
conv3d_3 (Conv3D)            (None, 2, 21, 21, 16)     2064
_________________________________________________________________
batch_normalization_3 (Batch (None, 2, 21, 21, 16)     64
_________________________________________________________________
activation_3 (Activation)    (None, 2, 21, 21, 16)     0
_________________________________________________________________
max_pooling3d_3 (MaxPooling3 (None, 2, 10, 10, 16)     0
_________________________________________________________________
conv3d_4 (Conv3D)            (None, 2, 8, 8, 32)       4640
_________________________________________________________________
batch_normalization_4 (Batch (None, 2, 8, 8, 32)       128
_________________________________________________________________
activation_4 (Activation)    (None, 2, 8, 8, 32)       0
_________________________________________________________________
max_pooling3d_4 (MaxPooling3 (None, 2, 4, 4, 32)       0
_________________________________________________________________
conv3d_5 (Conv3D)            (None, 2, 2, 2, 64)       18496
_________________________________________________________________
batch_normalization_5 (Batch (None, 2, 2, 2, 64)       256
_________________________________________________________________
activation_5 (Activation)    (None, 2, 2, 2, 64)       0
_________________________________________________________________
max_pooling3d_5 (MaxPooling3 (None, 2, 1, 1, 64)       0
_________________________________________________________________
flatten_1 (Flatten)          (None, 128)               0
_________________________________________________________________
frames (Dense)               (None, 4)                 516
=================================================================
Total params: 32,368
Trainable params: 32,120
Non-trainable params: 248
_________________________________________________________________
None
```

```
Epoch 0 / 50
Epoch Loss: 0.650, Epoch Accuracy: 0.183
Epoch 1 / 50
Epoch Loss: 0.577, Epoch Accuracy: 0.172
Epoch 2 / 50
Epoch Loss: 0.557, Epoch Accuracy: 0.182
Epoch 3 / 50
Epoch Loss: 0.562, Epoch Accuracy: 0.186
Epoch 4 / 50
Epoch Loss: 0.513, Epoch Accuracy: 0.232
Epoch 5 / 50
Epoch Loss: 0.520, Epoch Accuracy: 0.220
Epoch 6 / 50
Epoch Loss: 0.502, Epoch Accuracy: 0.243
Epoch 7 / 50
Epoch Loss: 0.446, Epoch Accuracy: 0.249
Epoch 8 / 50
Epoch Loss: 0.466, Epoch Accuracy: 0.264
Epoch 9 / 50
Epoch Loss: 0.461, Epoch Accuracy: 0.273
Epoch 10 / 50
Epoch Loss: 0.413, Epoch Accuracy: 0.295
Epoch 11 / 50
Epoch Loss: 0.426, Epoch Accuracy: 0.286
Epoch 12 / 50
Epoch Loss: 0.400, Epoch Accuracy: 0.328
Epoch 13 / 50
Epoch Loss: 0.372, Epoch Accuracy: 0.318
Epoch 14 / 50
Epoch Loss: 0.366, Epoch Accuracy: 0.324
Epoch 15 / 50
Epoch Loss: 0.373, Epoch Accuracy: 0.329
Epoch 16 / 50
Epoch Loss: 0.332, Epoch Accuracy: 0.342
Epoch 17 / 50
Epoch Loss: 0.341, Epoch Accuracy: 0.354
Epoch 18 / 50
Epoch Loss: 0.335, Epoch Accuracy: 0.339
Epoch 19 / 50
Epoch Loss: 0.350, Epoch Accuracy: 0.338
Epoch 20 / 50
Epoch Loss: 0.323, Epoch Accuracy: 0.359
Epoch 21 / 50
Epoch Loss: 0.311, Epoch Accuracy: 0.341
Epoch 22 / 50
Epoch Loss: 0.291, Epoch Accuracy: 0.377
Epoch 23 / 50
Epoch Loss: 0.301, Epoch Accuracy: 0.368
```

```
Epoch 24 / 50
Epoch Loss: 0.279, Epoch Accuracy: 0.372
Epoch 25 / 50
Epoch Loss: 0.268, Epoch Accuracy: 0.378
Epoch 26 / 50
Epoch Loss: 0.285, Epoch Accuracy: 0.377
Epoch 27 / 50
Epoch Loss: 0.306, Epoch Accuracy: 0.360
Epoch 28 / 50
Epoch Loss: 0.261, Epoch Accuracy: 0.372
Epoch 29 / 50
Epoch Loss: 0.291, Epoch Accuracy: 0.367
Epoch 30 / 50
Epoch Loss: 0.264, Epoch Accuracy: 0.381
Epoch 31 / 50
Epoch Loss: 0.262, Epoch Accuracy: 0.384
Epoch 32 / 50
Epoch Loss: 0.264, Epoch Accuracy: 0.378
Epoch 33 / 50
Epoch Loss: 0.273, Epoch Accuracy: 0.384
Epoch 34 / 50
Epoch Loss: 0.233, Epoch Accuracy: 0.395
Epoch 35 / 50
Epoch Loss: 0.241, Epoch Accuracy: 0.397
Epoch 36 / 50
Epoch Loss: 0.266, Epoch Accuracy: 0.367
Epoch 37 / 50
Epoch Loss: 0.275, Epoch Accuracy: 0.389
Epoch 38 / 50
Epoch Loss: 0.238, Epoch Accuracy: 0.390
Epoch 39 / 50
Epoch Loss: 0.243, Epoch Accuracy: 0.403
Epoch 40 / 50
Epoch Loss: 0.230, Epoch Accuracy: 0.380
Epoch 41 / 50
Epoch Loss: 0.251, Epoch Accuracy: 0.402
Epoch 42 / 50
Epoch Loss: 0.235, Epoch Accuracy: 0.396
Epoch 43 / 50
Epoch Loss: 0.227, Epoch Accuracy: 0.397
Epoch 44 / 50
Epoch Loss: 0.231, Epoch Accuracy: 0.393
Epoch 45 / 50
Epoch Loss: 0.246, Epoch Accuracy: 0.401
Epoch 46 / 50
Epoch Loss: 0.229, Epoch Accuracy: 0.395
Epoch 47 / 50
Epoch Loss: 0.222, Epoch Accuracy: 0.401
```

```
Epoch 48 / 50
Epoch Loss: 0.214, Epoch Accuracy: 0.408
Epoch 49 / 50
Epoch Loss: 0.195, Epoch Accuracy: 0.406
```





The accuracy starts to level out around 40% which is at least better than random guessing.

Now that the model is trained, we need some way to evaulate its performance on an entire video instead of just the *k*-frame clips that the model is trained to predict:

```
In [23]: from keras.models import model_from_json, Model

         def load_model(name):
             model_dir = 'models/'
             with open(model_dir + 'model_architecture.json%s' % name, 'r') as f:
                 model = model_from_json(f.read())
             # Load weights into the new model
             model.load_weights(model_dir + 'model_weights%s.h5' % name)
             return model
```

This code just allows us to load the model from a saved file instead of training it every time.

```
In [24]: model = load_model('grayscale')
```

The function below opens a speed video and splits it into the *k*-frame clips and runs each clip through the model to get a prediction for which frames contain jumps. The function returns the full one-hot label of the clip and the full prediction vector for each frame from many predictions.

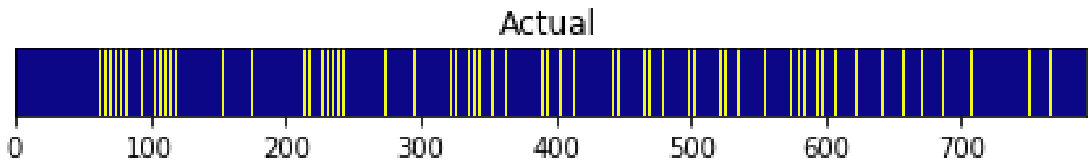
```
In [49]: def count_video(video_path, threshold=0.5):
             full_prediction = []
             full_label = []
```

```
        video = open_video(data_dir + video_dir + video_path, window_size=window_size)
        label_path = data_dir + annotation_dir + video_path.replace('.mp4', '.npy')
        label = np.load(label_path)
        start_frame = 0
        while start_frame < len(video) - window_size:
            clip = video[start_frame:start_frame + window_size]
            if use_flow_field:
                flow_field = video_to_flow_field(np.uint8(clip))
                label_clip = label[np.where(label < start_frame + window_size - 1)]
                label_clip = label_clip[np.where(label_clip > start_frame)]
                y = np.zeros(window_size - 1)
            else:
                label_clip = label[np.where(label < start_frame + window_size)]
                label_clip = label_clip[np.where(label_clip > start_frame)]
                y = np.zeros(window_size)
            for frame in label_clip:
                y[frame - start_frame] = 1
            full_label.append(y)
            if use_flow_field:
                y_pred = model.predict(np.expand_dims(flow_field, axis=0))
            else:
                y_pred = model.predict(np.expand_dims(clip, axis=0))
            y_pred[y_pred > threshold] = 1
            y_pred[y_pred <= threshold] = 0
            full_prediction.append(y_pred)
            start_frame += window_size
        full_prediction = np.reshape(full_prediction, (-1))
        full_label = np.reshape(full_label, (-1))
        ax = plt.subplot(211)
        ax.imshow(np.dstack([full_prediction] * 50)[0].T, cmap='plasma')
        ax.set_title('Predicted')
        ax.set_yticks([])
        ax = plt.subplot(212)
        ax.imshow(np.dstack([full_label] * 50)[0].T, cmap='plasma')
        ax.set_title('Actual')
        ax.set_yticks([])
        plt.tight_layout(0.8)
        plt.show()
        return full_label, full_prediction
```

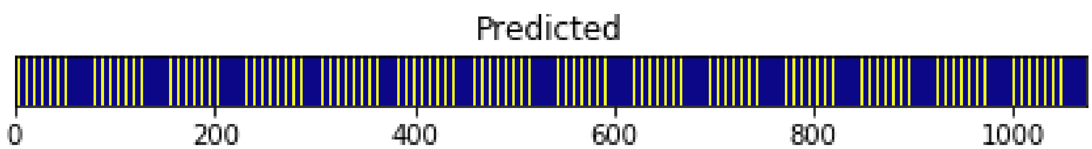
We'll test out our model on some of the sample videos:

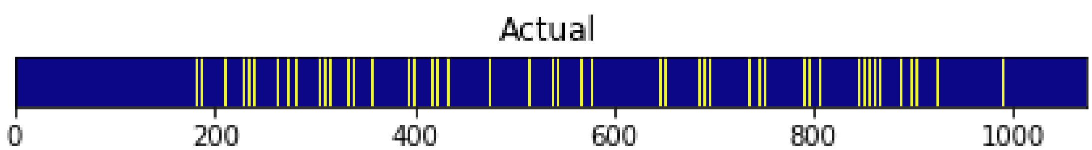
```
In [50]: for _ in range(5):
             video_path = np.random.choice(os.listdir(data_dir + video_dir))
             print(video_path)
             label, pred = count_video(video_path)
             print('Actual:', int(np.sum(label)), 'Predicted:', int(np.sum(pred)))
```

swe_1.mp4

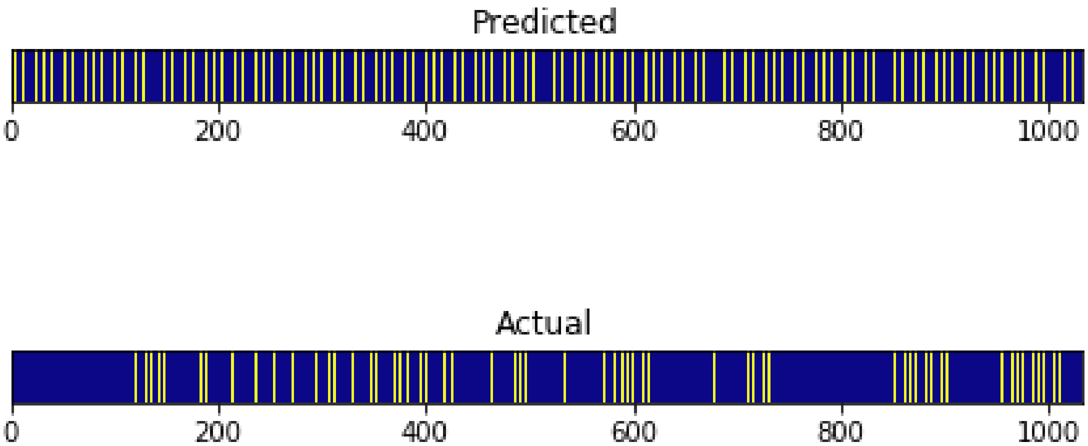


Actual: 124 Predicted: 198
korea_1.mp4

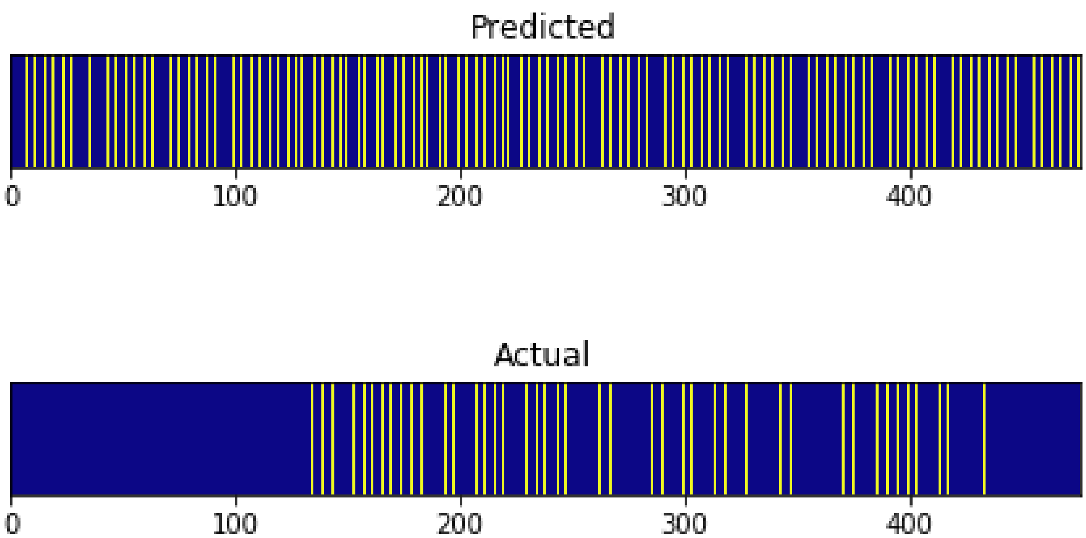




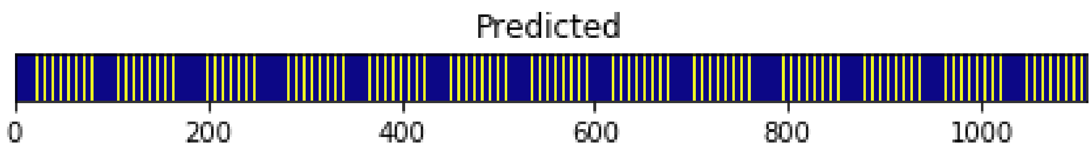
Actual: 136 Predicted: 268
us_5.mp4

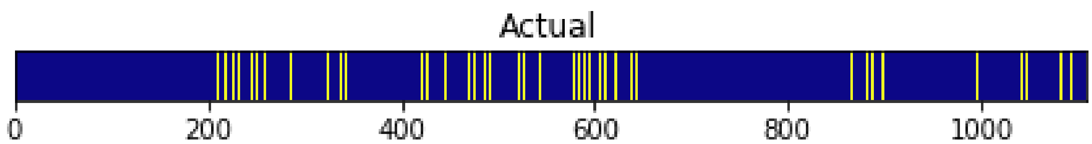



```
Actual: 145 Predicted: 258
jp_2.mp4
```




```
Actual: 50 Predicted: 119
us_4.mp4
```






```
Actual: 126 Predicted: 277
```

The grayscale model does not appear to perform very well. The main goal of this project however, is not to develop a perfect model which can achieve 100% accuracy. With such a small dataset it is unlikely that any model will be able to perform at the level of a trained human judge. The goal is to understand the inner workings of this particular method and hopefully find a direction to go in once more data can be collected. One way to do this is to visualize the intermediate activations of each 3D convolutional filter.

The function below creates a new model which outputs the activation of each convolution layer:

```
In [25]: def get_model_activations(clip):
             layer_outputs = [layer.output for layer in model.layers if 'activation' in layer.n
             activation_model = Model(inputs=model.input, outputs=layer_outputs)
             activations = activation_model.predict(np.expand_dims(clip, axis=0))

             return activations
```

Let's try it out on one of the videos from our dataset:

```
In [31]: video_path = 'hiro_1.mp4'
         print(video_path)
         clip, y = get_clip_and_label(video_path)
```

```
hiro_1.mp4
```

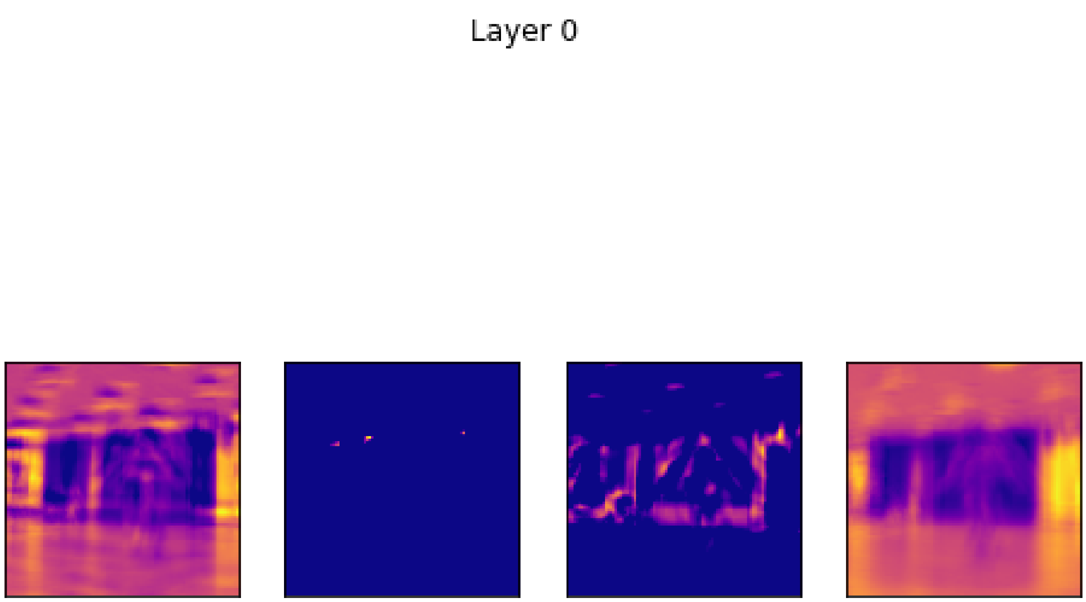
```
In [32]: interactive_plot = interactive(plot_frame(clip, y), i=(0, window_size - 1))
         output = interactive_plot.children[-1]
         output.layout.height = '360px'
         interactive_plot
```

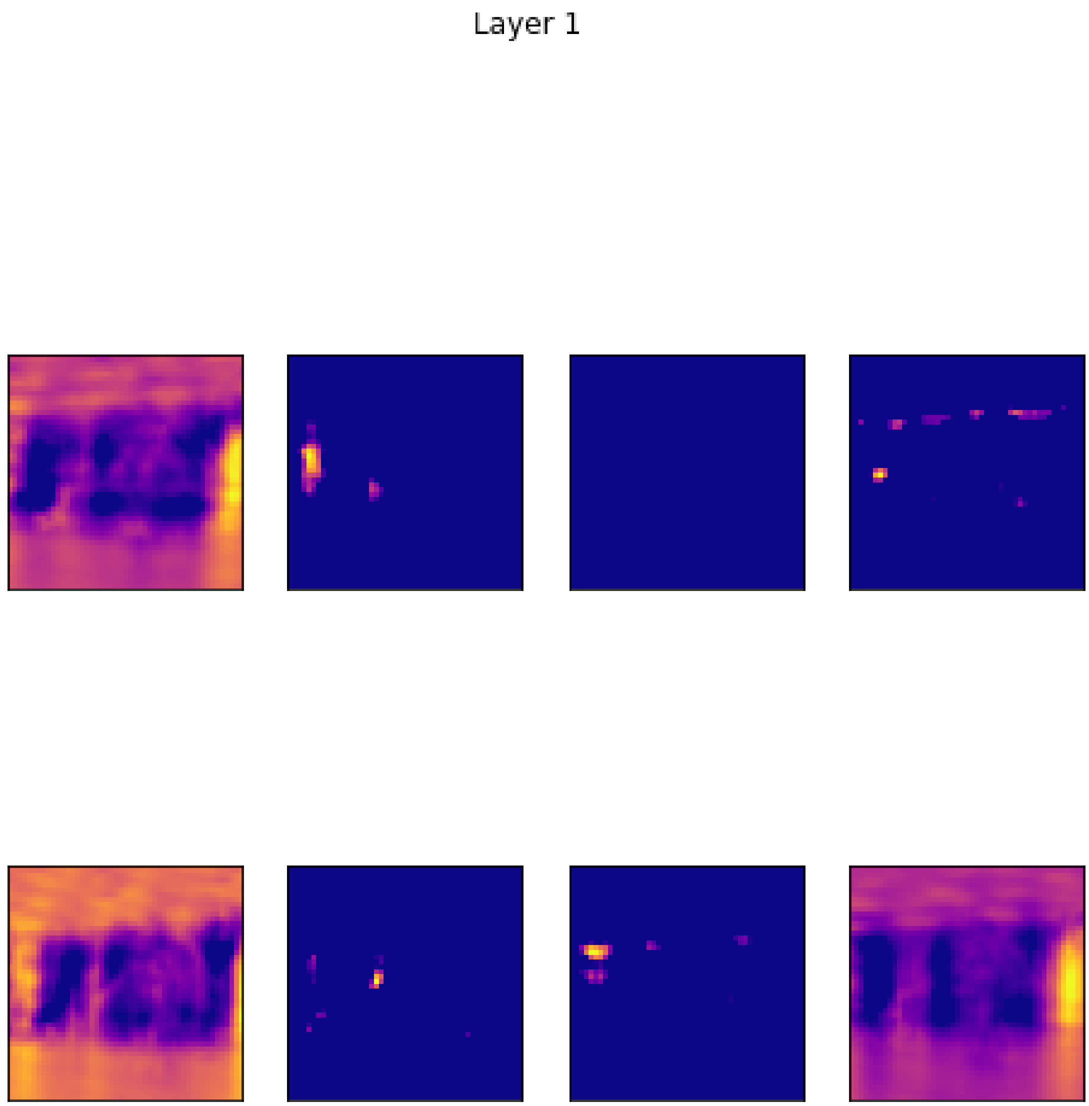
```
interactive(children=(IntSlider(value=1, description='i', max=3), Output(layout=Layout(height=
```

```
In [54]: activations = get_model_activations(clip)
```

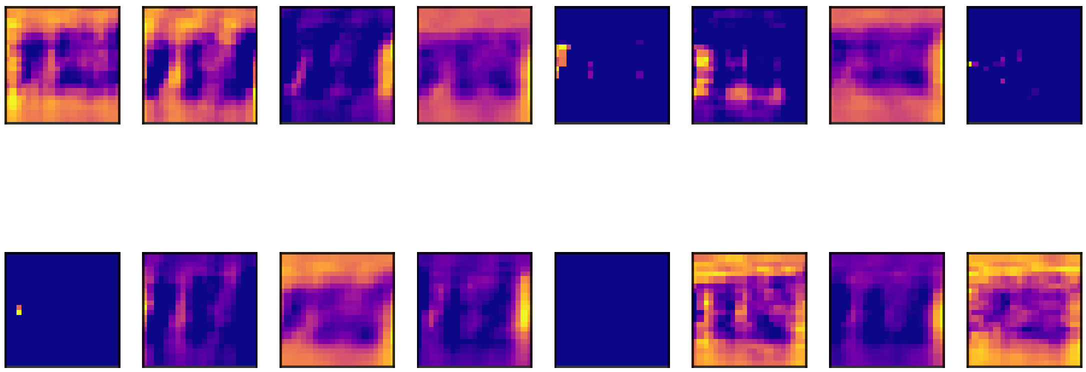
```
In [55]: import math

         fig = plt.figure(figsize=(8, 8))
         for i in range(len(activations)):
             fig = plt.figure(figsize=(8, 8))
             fig.suptitle('Layer %d' % i)
             num_filters = activations[i].shape[-1]
             rows = math.sqrt(num_filters)
             cols = num_filters // rows * 2
             for j in range(activations[i].shape[-1]):
                 ax = plt.subplot(rows, cols, j + 1)
                 ax.set_xticks([])
                 ax.set_yticks([])
                 ax.imshow(activations[i][0, 0, ..., j], cmap='plasma')
             plt.subplots_adjust(top=0.8)
             plt.show()
```

```
<Figure size 576x576 with 0 Axes>
```

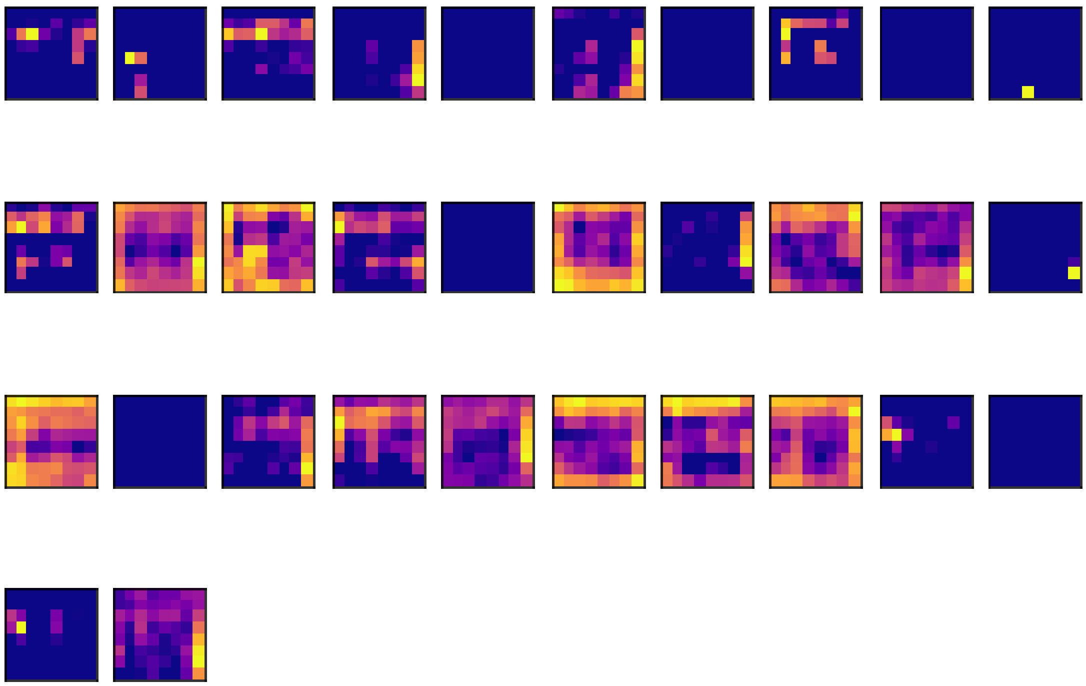



Layer 1

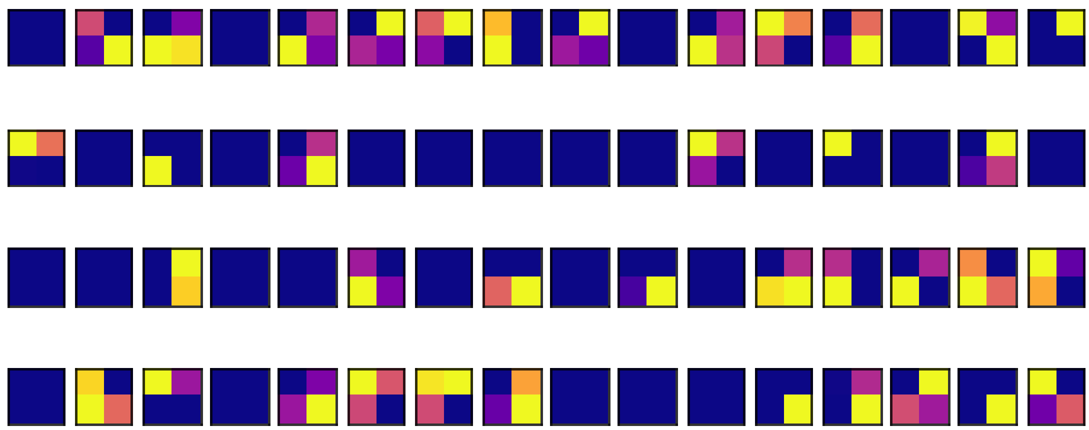
Layer 2



Layer 3



Layer 4



These plots are very difficult to interpret though. It doesn't appear that any of the activations are particularly focused on the area of the video containing the jumper until the 3rd layer and at this point our representation has been compressed so much that it's difficult to pull any meaning from these visualizations. Another way of visualization each filter's activation is to maximize each activation w.r.t the input space by applying gradient ascent at that particular layer:

```
In [33]: layer_dict = dict([(layer.name, layer) for layer in model.layers])
         print(layer_dict.keys())
```

```
dict_keys(['activation_1', 'batch_normalization_2', 'batch_normalization_3', 'batch_normalizat
```

The `layer_dict` above contains each layer of the model. Keras can compute the gradient at any layer allowing us to find the inputs which maximize the activations of certain filters.

First, since the input to our model is an abstract tensor, we need to be able to convert this into an RGB image:

```
In [34]: def deprocess_image(x):
             # normalize tensor: center on 0., ensure std is 0.1
             x -= x.mean()
             x /= (x.std() + 1e-5)
             x *= 0.1

             # clip to [0, 1]
             x += 0.5
```

```
        x = np.clip(x, 0, 1)

        # convert to RGB array
        x *= 255
        x = np.clip(x, 0, 255).astype('uint8')
        return x
```

Now we can define a function which takes a layer as input and produces a visualization of the inputs which maximize the filters of that layer:

```
In [35]: from keras import backend as K

         def plot_conv_layer(model, layer_name, layer_dict, input_video=None, vis_iter=50):
             visualizations = np.array([])
             layer_output = layer_dict[layer_name].output
             input_img = model.input
             rows = 3
             cols = 3
             num_filters = rows * cols
             vis_size = frame_size
             active_layers = 0  # keeps track of number of activated layers currently in the v
             filter_index = 0

             while active_layers < num_filters and 'video' not in layer_name:
                 if input_video is None:
                     if use_flow_field:
                         noise_batch = np.random.random((1, window_size - 1, vis_size, vis_siz
                     elif grayscale:
                         noise_batch = np.random.normal(1, size=(1, window_size, vis_size, vis
                     else:
                         noise_batch = np.random.normal(1, size=(1, window_size, vis_size, vis
                 else:
                     noise_batch = input_video
                 # build a loss function that maximizes the activation
                 # of the nth filter of the layer considered
                 try:
                     loss = K.mean(layer_output[..., filter_index])
                 except Exception as e:
                     layer_output = layer_dict[layer_name].output
                     filter_index = 0
                     pass

                 # compute the gradient of the input picture wrt this loss
                 grads = K.gradients(loss, input_img)[0]

                 # normalize the gradient
                 grads /= (K.sqrt(K.mean(K.square(grads))) + 1e-5)
```

```
        # this function returns the loss and gradients given the input picture
        iterate = K.function([input_img], [loss, grads])

        filter_index += 1

        step = 1.
        # run gradient ascent for 20 steps
        for i in range(vis_iter):
            loss_value, grads_value = iterate([noise_batch])
            if loss_value == 0:
                break
            noise_batch += grads_value * step
        if loss_value != 0:
            active_layers += 1
            print(active_layers, '/', num_filters)
            visualizations = np.append(visualizations, noise_batch)

    if use_flow_field:
        print(visualizations.shape)
        visualizations = np.reshape(visualizations, (num_filters, 1, window_size - 1,
    elif grayscale:
        visualizations = np.reshape(visualizations, (num_filters, 1, window_size, vis_
    else:
        visualizations = np.reshape(visualizations, (num_filters, 1, window_size, vis_
    frame_offset = 0
    if use_flow_field:
        frame_offset = -1

    return visualizations
```

```
In [65]: def plot_filters(visualizations, layer_name, grayscale, use_flow_field, save_filters=F
    def f(i):
        fig, axes = plt.subplots(3, 3, figsize=(6,6))
        for filter_i in range(visualizations.shape[0]):
            r = int(filter_i // 3)
            c = int(filter_i % 3)
            frame = visualizations[filter_i][0][i]
            save_dir = ''
            if use_flow_field:
                img = flow_to_rgb(np.float32(frame))
                axes[r][c].imshow(img)
                save_dir = 'flow'
            elif grayscale:
                #img = deprocess_image(frame)
                img = np.reshape(frame, (frame_size, frame_size))
                axes[r][c].imshow(img, cmap='plasma')
                save_dir = 'grayscale'
            else:
```

```
                img = deprocess_image(frame)
                img = np.reshape(img, (frame_size, frame_size, 3))
                axes[r][c].imshow(img)
                save_dir = 'rgb'
            axes[r][c].set_title(str(filter_i))
            axes[r][c].set_xticks([])
            axes[r][c].set_yticks([])
        fig.suptitle(layer_name)
        plt.tight_layout()
        plt.subplots_adjust(top=0.8)
        if save_filters:
            try:
                os.mkdir('conv_vis')
            except FileExistsError:
                pass
            try:
                os.mkdir('conv_vis/%s' % save_dir)
            except FileExistsError:
                pass
            try:
                os.mkdir('conv_vis/%s/%s' % (save_dir, layer_name))
            except FileExistsError:
                pass
            fig.savefig('conv_vis/' + save_dir + '/%s/%d.png' % (layer_name, i), dpi=
    return f
```

In [37]:
```
grayscale_filter_images = []
layer_names = []

for layer in layer_dict.keys():
    if 'activation' in layer:
        try:
            layer_names.append(layer)
            visualizations = plot_conv_layer(model, layer, layer_dict, vis_iter=15)
            grayscale_filter_images.append(visualizations)
        except Exception as e:
            pass
```

```
1 / 9
2 / 9
3 / 9
4 / 9
5 / 9
6 / 9
7 / 9
8 / 9
9 / 9
1 / 9
```

```
2 / 9
3 / 9
4 / 9
5 / 9
6 / 9
7 / 9
8 / 9
9 / 9
1 / 9
2 / 9
3 / 9
4 / 9
5 / 9
6 / 9
7 / 9
8 / 9
9 / 9
1 / 9
2 / 9
3 / 9
4 / 9
5 / 9
6 / 9
7 / 9
8 / 9
9 / 9
1 / 9
2 / 9
3 / 9
4 / 9
5 / 9
6 / 9
7 / 9
8 / 9
9 / 9
```

I wanted to use interactive plots to display these visualizations but they are very slow and usually do not persist after closing the notebook. If the figures below are empty I have also saved each frame and display them as animations with interpretations after each of these sections for each model.

In [63]:
```
save_filters = True  # set to True to save filter visualizations for display later
```

In [66]:
```
vis_i = 0
interactive_plot = interactive(plot_filters(grayscale_filter_images[vis_i], layer_name
output = interactive_plot.children[-1]
output.layout.height = '480px'
```

```
        vis_i += 1
        interactive_plot
```

```
interactive(children=(IntSlider(value=1, description='i', max=3), Output(layout=Layout(height=
```

```
In [67]: interactive_plot = interactive(plot_filters(grayscale_filter_images[vis_i], layer_name
         output = interactive_plot.children[-1]
         output.layout.height = '480px'
         vis_i += 1
         interactive_plot
```

```
interactive(children=(IntSlider(value=1, description='i', max=3), Output(layout=Layout(height=
```

```
In [68]: interactive_plot = interactive(plot_filters(grayscale_filter_images[vis_i], layer_name
         output = interactive_plot.children[-1]
         output.layout.height = '480px'
         vis_i += 1
         interactive_plot
```

```
interactive(children=(IntSlider(value=1, description='i', max=3), Output(layout=Layout(height=
```

```
In [69]: interactive_plot = interactive(plot_filters(grayscale_filter_images[vis_i], layer_name
         output = interactive_plot.children[-1]
         output.layout.height = '480px'
         vis_i += 1
         interactive_plot
```

```
interactive(children=(IntSlider(value=1, description='i', max=3), Output(layout=Layout(height=
```

```
In [70]: interactive_plot = interactive(plot_filters(grayscale_filter_images[vis_i], layer_name
         output = interactive_plot.children[-1]
         output.layout.height = '480px'
         vis_i += 1
         interactive_plot
```

```
interactive(children=(IntSlider(value=1, description='i', max=3), Output(layout=Layout(height=
```

A good way to visualize the motion that each filter has captured is to play them back as animations. For this I am displaying each 'frame' of the filter at 15fps and looping forward and backward:

```
In [2]: %%HTML
        <img src="figures/filters/grayscale/activation_1.gif" width="360" height="360" />
```

```
<IPython.core.display.HTML object>
```

In [3]:
```
%%HTML
<img src="figures/filters/grayscale/activation_2.gif" width="360" height="360" />
```

```
<IPython.core.display.HTML object>
```

In [4]:
```
%%HTML
<img src="figures/filters/grayscale/activation_3.gif" width="360" height="360" />
```

```
<IPython.core.display.HTML object>
```

In [5]:
```
%%HTML
<img src="figures/filters/grayscale/activation_4.gif" width="360" height="360" />
```

```
<IPython.core.display.HTML object>
```

In [6]:
```
%%HTML
<img src="figures/filters/grayscale/activation_5.gif" width="360" height="360" />
```

```
<IPython.core.display.HTML object>
```

It seems that the first couple layers are trying to pick up on large scale motion in the video such as the camera moving. Deeper layers, by my own interpretation, start to resemble feet passing by each other from different angles indicating that the model did learn an inner representation of what a jump looks like within a small window of frames.

Now we will try to train a model by first converting each input video into a vector field representing dense optical flow using an `OpenCV` implementation of Gunner Farneback's algorithm (https://docs.opencv.org/3.1.0/d7/d8b/tutorial_py_lucas_kanade.html)

In [90]:
```
grayscale = False
use_flow_field = True
window_size = 5
```

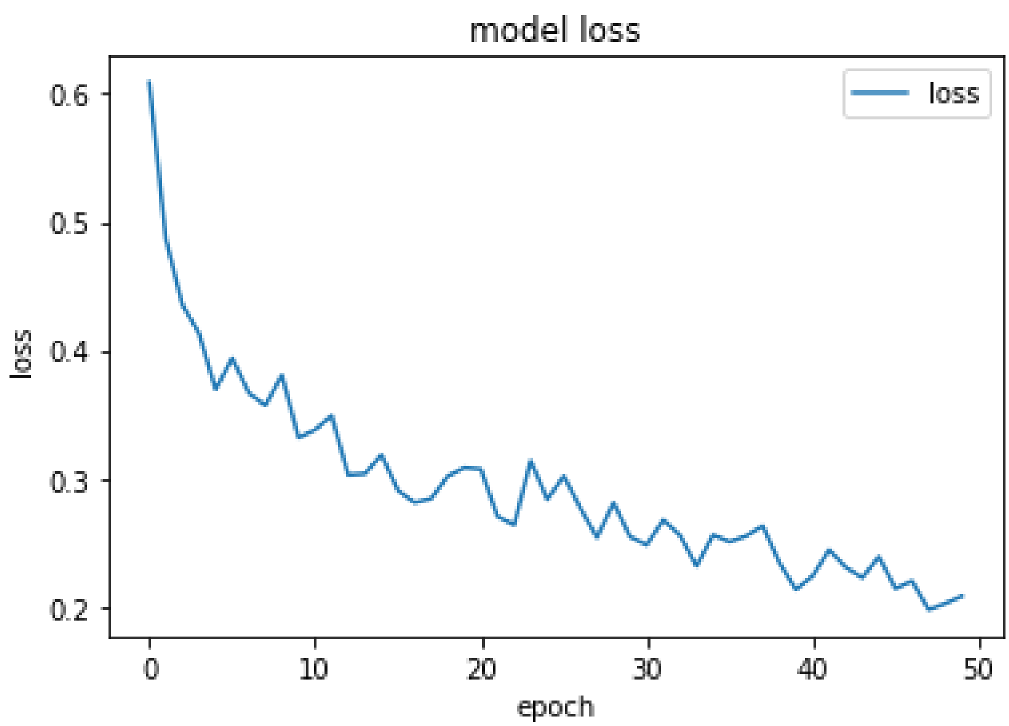
In [86]:
```
np.random.seed(42)

counter = SpeedCounter(data_dir=os.getcwd() + '/data/',
                       video_dir='speed_videos/',
                       annotation_dir='speed_annotations/',
                       lr=1e-3,
                       batch_size=32,
                       n_epochs=50,
                       frame_size=128,
                       window_size=window_size,
                       use_flow_field=use_flow_field,
                       grayscale=grayscale,
                       verbose=False)

# uncomment to re-train model
#counter.train()
```

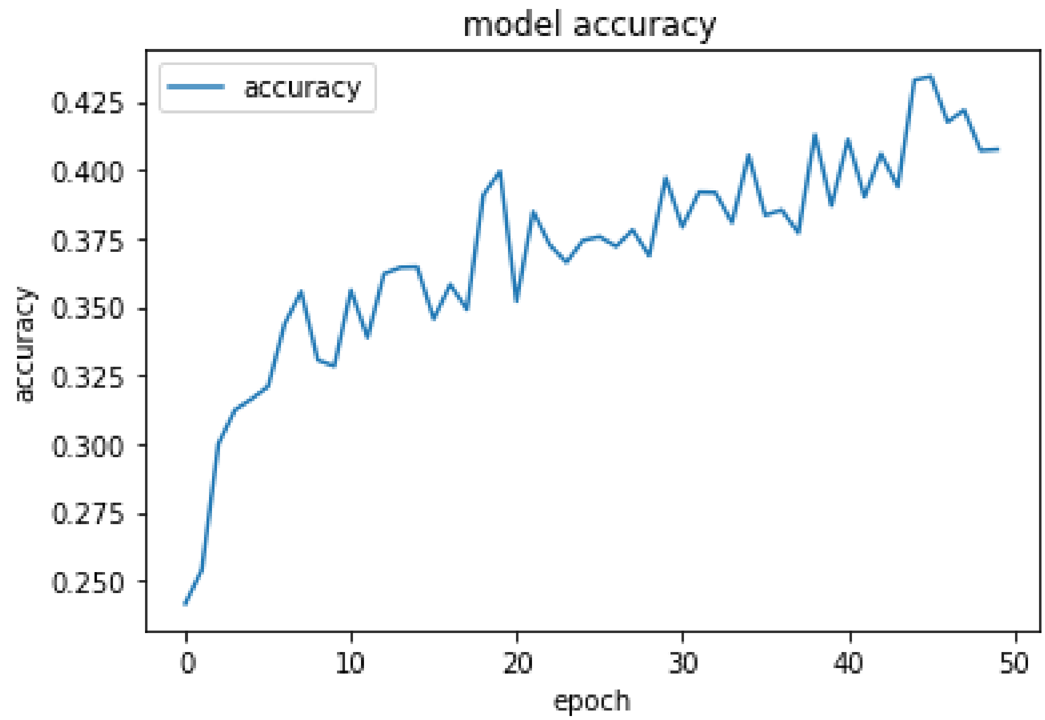
```
Total Frames: 14415
Total Samples: 2883
Model: "model_8"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
video (InputLayer)           (None, 4, 128, 128, 2)    0
_________________________________________________________________
conv3d_21 (Conv3D)           (None, 3, 113, 113, 4)    4100
_________________________________________________________________
batch_normalization_21 (Batc (None, 3, 113, 113, 4)    16
_________________________________________________________________
activation_21 (Activation)   (None, 3, 113, 113, 4)    0
_________________________________________________________________
max_pooling3d_21 (MaxPooling (None, 3, 56, 56, 4)      0
_________________________________________________________________
conv3d_22 (Conv3D)           (None, 2, 49, 49, 8)      4104
_________________________________________________________________
batch_normalization_22 (Batc (None, 2, 49, 49, 8)      32
_________________________________________________________________
activation_22 (Activation)   (None, 2, 49, 49, 8)      0
_________________________________________________________________
max_pooling3d_22 (MaxPooling (None, 2, 24, 24, 8)      0
_________________________________________________________________
conv3d_23 (Conv3D)           (None, 2, 21, 21, 16)     2064
_________________________________________________________________
batch_normalization_23 (Batc (None, 2, 21, 21, 16)     64
_________________________________________________________________
activation_23 (Activation)   (None, 2, 21, 21, 16)     0
_________________________________________________________________
max_pooling3d_23 (MaxPooling (None, 2, 10, 10, 16)     0
_________________________________________________________________
conv3d_24 (Conv3D)           (None, 2, 8, 8, 32)       4640
_________________________________________________________________
batch_normalization_24 (Batc (None, 2, 8, 8, 32)       128
_________________________________________________________________
activation_24 (Activation)   (None, 2, 8, 8, 32)       0
_________________________________________________________________
max_pooling3d_24 (MaxPooling (None, 2, 4, 4, 32)       0
_________________________________________________________________
conv3d_25 (Conv3D)           (None, 2, 2, 2, 64)       18496
_________________________________________________________________
batch_normalization_25 (Batc (None, 2, 2, 2, 64)       256
_________________________________________________________________
activation_25 (Activation)   (None, 2, 2, 2, 64)       0
_________________________________________________________________
max_pooling3d_25 (MaxPooling (None, 2, 1, 1, 64)       0
_________________________________________________________________
```

```
flatten_5 (Flatten)          (None, 128)              0
_________________________________________________________________
frames (Dense)               (None, 4)                516
=================================================================
Total params: 34,416
Trainable params: 34,168
Non-trainable params: 248
_________________________________________________________________
None
Epoch 0 / 50
Epoch Loss: 0.609, Epoch Accuracy: 0.242
Epoch 1 / 50
Epoch Loss: 0.487, Epoch Accuracy: 0.254
Epoch 2 / 50
Epoch Loss: 0.436, Epoch Accuracy: 0.300
Epoch 3 / 50
Epoch Loss: 0.413, Epoch Accuracy: 0.312
Epoch 4 / 50
Epoch Loss: 0.370, Epoch Accuracy: 0.316
Epoch 5 / 50
Epoch Loss: 0.394, Epoch Accuracy: 0.321
Epoch 6 / 50
Epoch Loss: 0.367, Epoch Accuracy: 0.344
Epoch 7 / 50
Epoch Loss: 0.357, Epoch Accuracy: 0.356
Epoch 8 / 50
Epoch Loss: 0.381, Epoch Accuracy: 0.331
Epoch 9 / 50
Epoch Loss: 0.332, Epoch Accuracy: 0.328
Epoch 10 / 50
Epoch Loss: 0.338, Epoch Accuracy: 0.356
Epoch 11 / 50
Epoch Loss: 0.349, Epoch Accuracy: 0.339
Epoch 12 / 50
Epoch Loss: 0.303, Epoch Accuracy: 0.362
Epoch 13 / 50
Epoch Loss: 0.304, Epoch Accuracy: 0.364
Epoch 14 / 50
Epoch Loss: 0.319, Epoch Accuracy: 0.365
Epoch 15 / 50
Epoch Loss: 0.291, Epoch Accuracy: 0.346
Epoch 16 / 50
Epoch Loss: 0.281, Epoch Accuracy: 0.358
Epoch 17 / 50
Epoch Loss: 0.284, Epoch Accuracy: 0.349
Epoch 18 / 50
Epoch Loss: 0.302, Epoch Accuracy: 0.391
Epoch 19 / 50
```

```
Epoch Loss: 0.309, Epoch Accuracy: 0.400
Epoch 20 / 50
Epoch Loss: 0.307, Epoch Accuracy: 0.352
Epoch 21 / 50
Epoch Loss: 0.271, Epoch Accuracy: 0.385
Epoch 22 / 50
Epoch Loss: 0.264, Epoch Accuracy: 0.373
Epoch 23 / 50
Epoch Loss: 0.314, Epoch Accuracy: 0.366
Epoch 24 / 50
Epoch Loss: 0.284, Epoch Accuracy: 0.374
Epoch 25 / 50
Epoch Loss: 0.302, Epoch Accuracy: 0.376
Epoch 26 / 50
Epoch Loss: 0.277, Epoch Accuracy: 0.372
Epoch 27 / 50
Epoch Loss: 0.254, Epoch Accuracy: 0.378
Epoch 28 / 50
Epoch Loss: 0.281, Epoch Accuracy: 0.369
Epoch 29 / 50
Epoch Loss: 0.255, Epoch Accuracy: 0.397
Epoch 30 / 50
Epoch Loss: 0.248, Epoch Accuracy: 0.379
Epoch 31 / 50
Epoch Loss: 0.268, Epoch Accuracy: 0.392
Epoch 32 / 50
Epoch Loss: 0.256, Epoch Accuracy: 0.392
Epoch 33 / 50
Epoch Loss: 0.232, Epoch Accuracy: 0.381
Epoch 34 / 50
Epoch Loss: 0.256, Epoch Accuracy: 0.406
Epoch 35 / 50
Epoch Loss: 0.251, Epoch Accuracy: 0.384
Epoch 36 / 50
Epoch Loss: 0.255, Epoch Accuracy: 0.385
Epoch 37 / 50
Epoch Loss: 0.263, Epoch Accuracy: 0.377
Epoch 38 / 50
Epoch Loss: 0.235, Epoch Accuracy: 0.413
Epoch 39 / 50
Epoch Loss: 0.213, Epoch Accuracy: 0.387
Epoch 40 / 50
Epoch Loss: 0.224, Epoch Accuracy: 0.411
Epoch 41 / 50
Epoch Loss: 0.244, Epoch Accuracy: 0.390
Epoch 42 / 50
Epoch Loss: 0.231, Epoch Accuracy: 0.406
Epoch 43 / 50
```

```
Epoch Loss: 0.223, Epoch Accuracy: 0.394
Epoch 44 / 50
Epoch Loss: 0.239, Epoch Accuracy: 0.433
Epoch 45 / 50
Epoch Loss: 0.214, Epoch Accuracy: 0.434
Epoch 46 / 50
Epoch Loss: 0.220, Epoch Accuracy: 0.418
Epoch 47 / 50
Epoch Loss: 0.198, Epoch Accuracy: 0.422
Epoch 48 / 50
Epoch Loss: 0.203, Epoch Accuracy: 0.407
Epoch 49 / 50
Epoch Loss: 0.208, Epoch Accuracy: 0.408
```



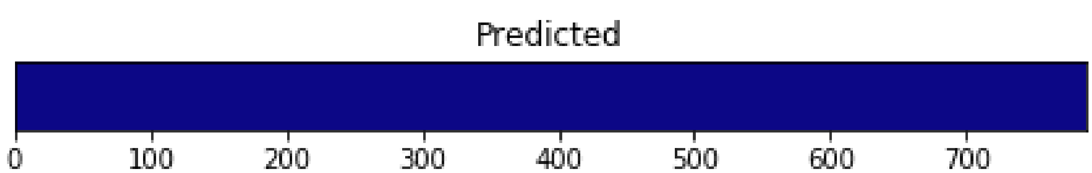


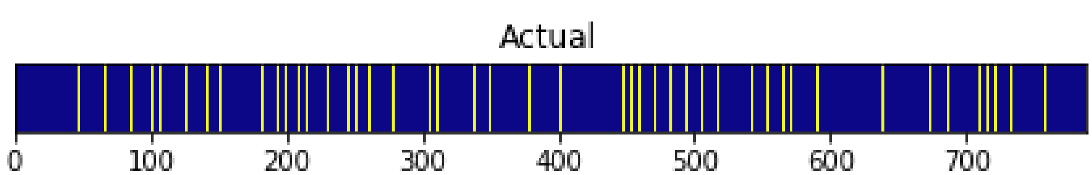
Similarly, the model accuracy does not increase much beyond 40%

```
In [91]: model = load_model('flow')
```

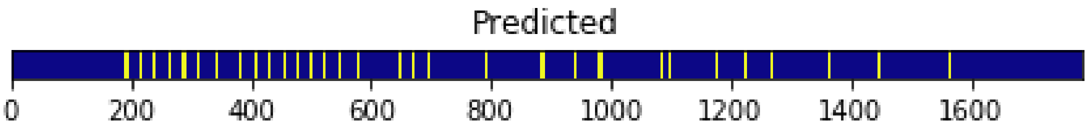
```
In [88]: for _ in range(5):
             video_path = np.random.choice(os.listdir(data_dir + video_dir))
             print(video_path)
             label, pred = count_video(video_path, threshold=0.8)
             print('Actual:', int(np.sum(label)), 'Predicted:', int(np.sum(pred)))
```

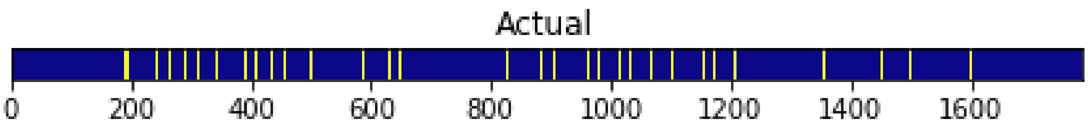
```
us_3.mp4
```



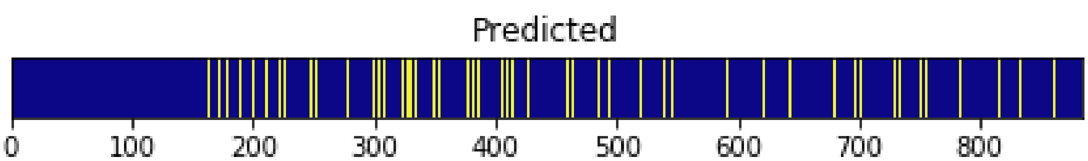


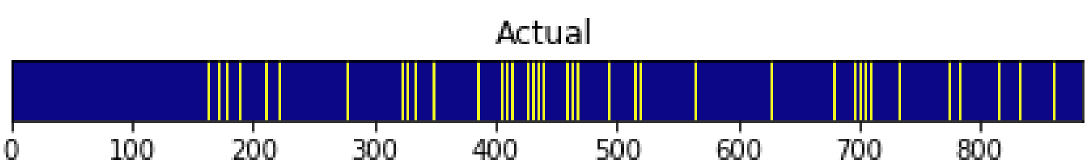
```
Actual: 77 Predicted: 0
us_1.mp4
```



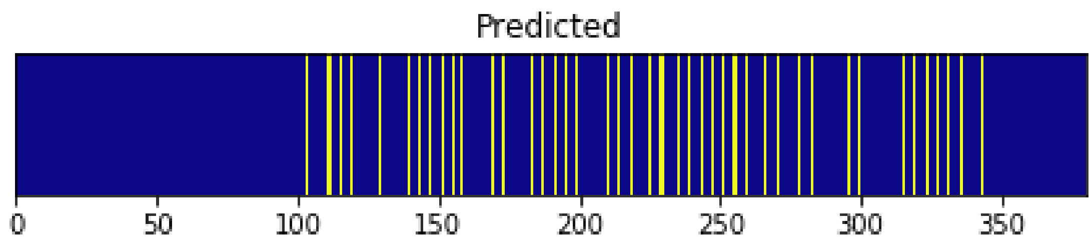


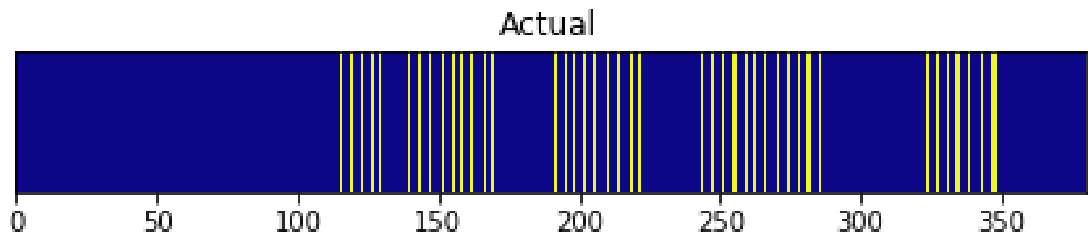

```
Actual: 148 Predicted: 137
us_4.mp4
```



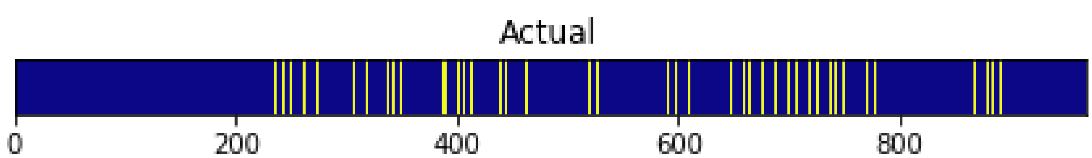



```
Actual: 109 Predicted: 119
jp_2.mp4
```






```
Actual: 42 Predicted: 43
jp_1.mp4
```




```
Actual: 105 Predicted: 89
```

Performance across full videos however has significantly improved compared to the grayscale model. This is likely because the accuracy measures if the model got the frame prediction exactly right, however to accurately count a full video we only have to classify each k-frame window as having *a* jump. So even if the model is off by a frame or two, it is technically a correct prediction.

```
In [92]: video_path = 'hiro_1.mp4'
         print(video_path)
         clip, y = get_clip_and_label(video_path)
```

```
hiro_1.mp4
```

```
In [93]: interactive_plot = interactive(plot_frame(clip, y), i=(0, window_size - 2))
         output = interactive_plot.children[-1]
         output.layout.height = '360px'
         interactive_plot
```

```
interactive(children=(IntSlider(value=1, description='i', max=3), Output(layout=Layout(height=
```

We can visualize this dense optical flow by converting the magnitude to intensity and direction to color values. Interestingly, the densest motion during the spike of the jump is around the jumper's wrists.

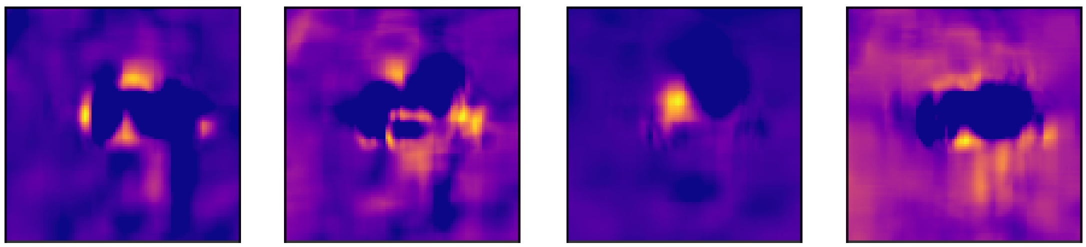
```
In [91]: activations = get_model_activations(clip)
```

One main downside to this method is that beyond the first layer, all activations only have 1 'frame' (i.e their 3rd time axis is flattened after the first two convolutions)

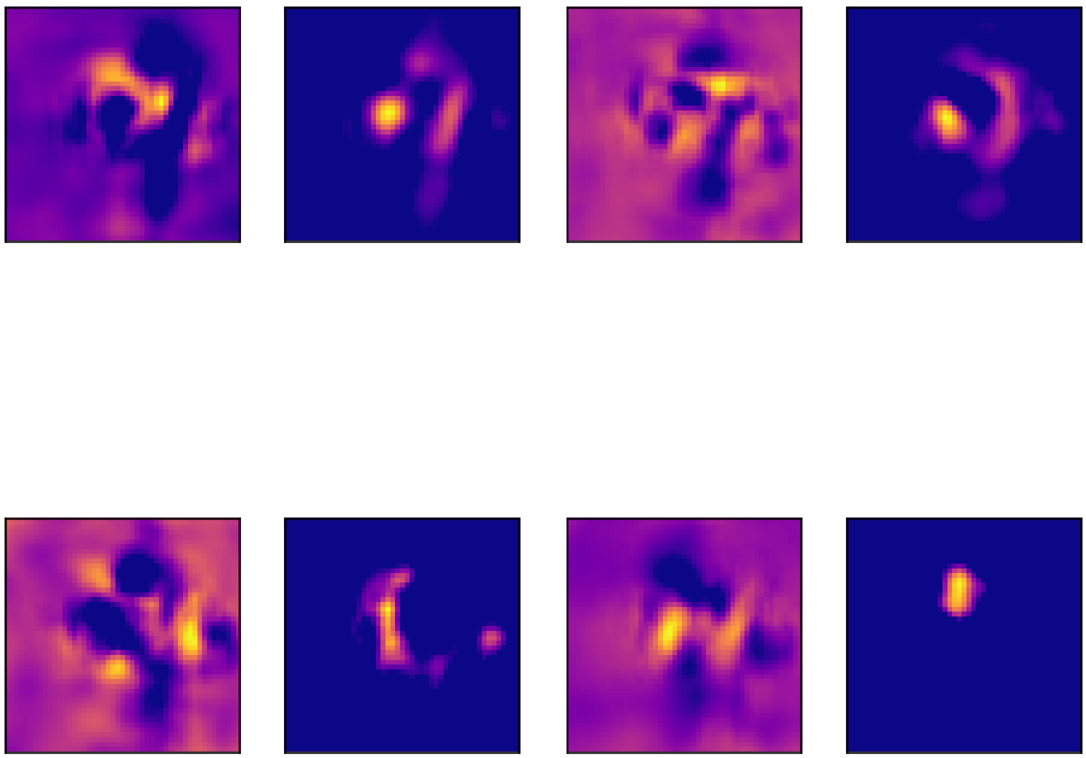
```
In [92]: import math

         fig = plt.figure(figsize=(8, 8))
         for i in range(len(activations)):
             fig = plt.figure(figsize=(8, 8))
             fig.suptitle('Layer %d' % i)
             num_filters = activations[i].shape[-1]
             rows = math.sqrt(num_filters)
             cols = num_filters // rows * 2
             for j in range(activations[i].shape[-1]):
                 ax = plt.subplot(rows, cols, j + 1)
                 ax.set_xticks([])
                 ax.set_yticks([])
                 ax.imshow(activations[i][0, 0, ..., j], cmap='plasma')
             plt.subplots_adjust(top=0.8)
             plt.show()
```

```
<Figure size 576x576 with 0 Axes>
```

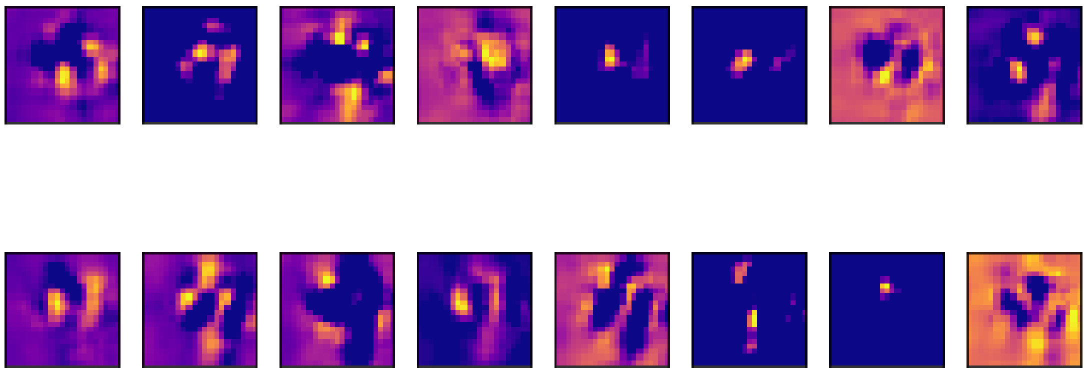
Layer 0



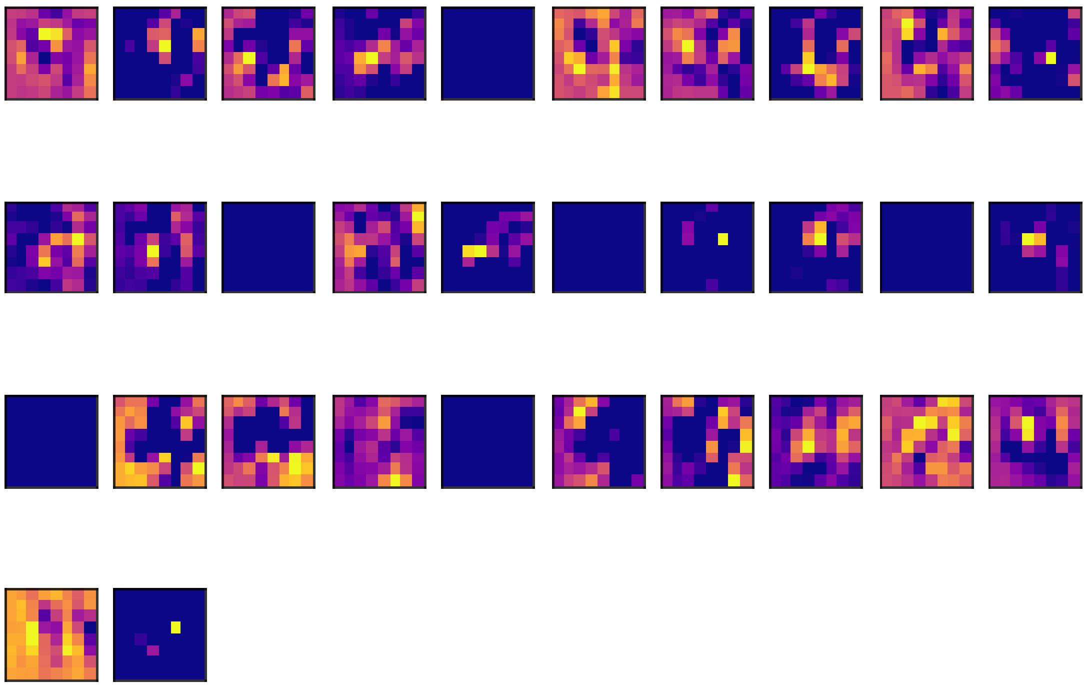
Layer 1

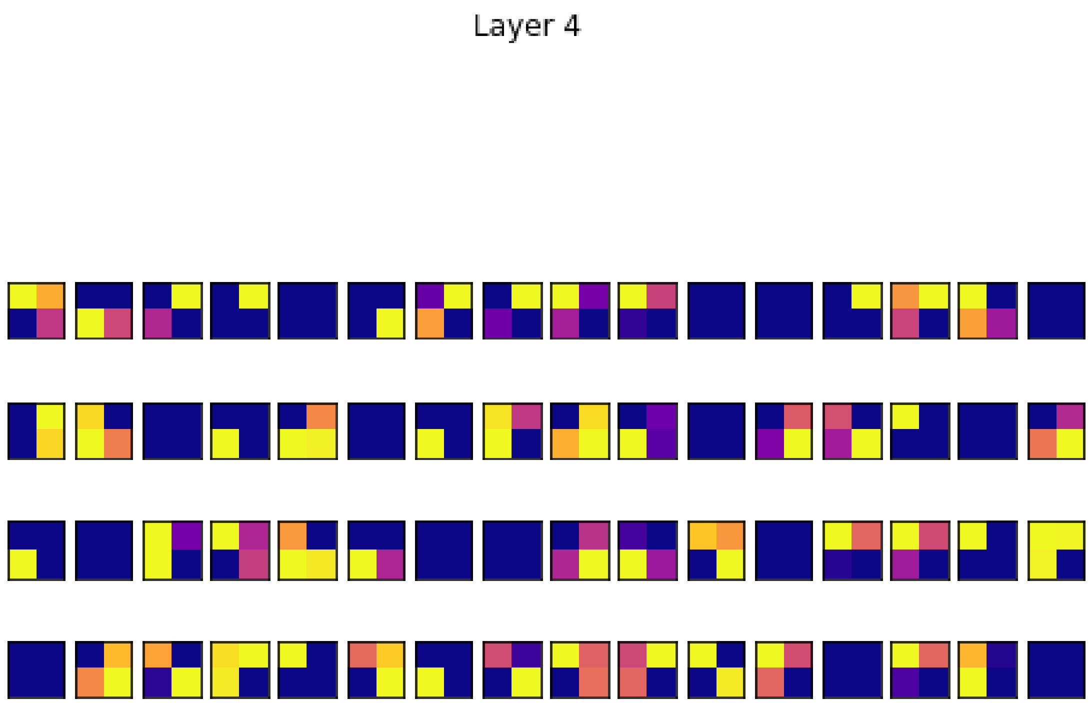


Layer 2



Layer 3





Compared to the grayscale model's activations, these seem a little more interpretable. The main areas of activation seem to be where the motion is densest such as the arms and legs. This is interesting since human judges exclusively count based on the jumper's feet, but the wrists and rope motion can also give a lot of useful information which it appears the model is picking up on.

Let's visualize the input space maximized w.r.t the layer activations:

```
In [94]: layer_dict = dict([(layer.name, layer) for layer in model.layers])
         print(layer_dict.keys())
```

```
dict_keys(['batch_normalization_22', 'max_pooling3d_23', 'video', 'flatten_5', 'conv3d_24', 'ma
```

```
In [95]: flow_filter_images = []
         layer_names = []

         for layer in layer_dict.keys():
             if 'activation' in layer:
                 try:
                     layer_names.append(layer)
                     visualizations = plot_conv_layer(model, layer, layer_dict, vis_iter=15)
                     flow_filter_images.append(visualizations)
                 except Exception as e:
                     print(e)
                     pass
```

```
1 / 9
2 / 9
3 / 9
4 / 9
5 / 9
6 / 9
7 / 9
8 / 9
9 / 9
(1179648,)
1 / 9
2 / 9
3 / 9
4 / 9
5 / 9
6 / 9
7 / 9
8 / 9
9 / 9
(1179648,)
1 / 9
2 / 9
3 / 9
4 / 9
5 / 9
6 / 9
7 / 9
8 / 9
9 / 9
(1179648,)
1 / 9
2 / 9
3 / 9
4 / 9
5 / 9
6 / 9
7 / 9
8 / 9
9 / 9
(1179648,)
1 / 9
2 / 9
3 / 9
4 / 9
5 / 9
6 / 9
7 / 9
8 / 9
```

```
9 / 9
(1179648,)
```

In [97]:
```
vis_i = 0
interactive_plot = interactive(plot_filters(flow_filter_images[vis_i], layer_names[vi
output = interactive_plot.children[-1]
output.layout.height = '480px'
vis_i += 1
interactive_plot
```

```
interactive(children=(IntSlider(value=1, description='i', max=3), Output(layout=Layout(height=
```

In [98]:
```
interactive_plot = interactive(plot_filters(flow_filter_images[vis_i], layer_names[vi
output = interactive_plot.children[-1]
output.layout.height = '480px'
vis_i += 1
interactive_plot
```

```
interactive(children=(IntSlider(value=1, description='i', max=3), Output(layout=Layout(height=
```

In [99]:
```
interactive_plot = interactive(plot_filters(flow_filter_images[vis_i], layer_names[vi
output = interactive_plot.children[-1]
output.layout.height = '480px'
vis_i += 1
interactive_plot
```

```
interactive(children=(IntSlider(value=1, description='i', max=3), Output(layout=Layout(height=
```

In [100]:
```
interactive_plot = interactive(plot_filters(flow_filter_images[vis_i], layer_names[v
output = interactive_plot.children[-1]
output.layout.height = '480px'
vis_i += 1
interactive_plot
```

```
interactive(children=(IntSlider(value=1, description='i', max=3), Output(layout=Layout(height=
```

In [101]:
```
interactive_plot = interactive(plot_filters(flow_filter_images[vis_i], layer_names[v
output = interactive_plot.children[-1]
output.layout.height = '480px'
vis_i += 1
interactive_plot
```

```
interactive(children=(IntSlider(value=1, description='i', max=3), Output(layout=Layout(height=
```

```
In [7]: %%HTML
        <img src="figures/filters/flow/activation_21.gif" width="360" height="360" />
```

<IPython.core.display.HTML object>

```
In [8]: %%HTML
        <img src="figures/filters/flow/activation_22.gif" width="360" height="360" />
```

<IPython.core.display.HTML object>

```
In [9]: %%HTML
        <img src="figures/filters/flow/activation_23.gif" width="360" height="360" />
```

<IPython.core.display.HTML object>

```
In [10]: %%HTML
         <img src="figures/filters/flow/activation_24.gif" width="360" height="360" />
```

<IPython.core.display.HTML object>

```
In [11]: %%HTML
         <img src="figures/filters/flow/activation_25.gif" width="360" height="360" />
```

<IPython.core.display.HTML object>

These are much harder to interpret than the grayscale model visualizations. The first layer has abstract patterns similar to the first layer of the grayscale model but beyond that these do not appear to resemble a human-interpretable representation of a jump, even though the model is able to out-perform the grayscale model.

Finally, let's try to build a model that sees the raw video in color:

```
In [107]: use_flow_field = False
          grayscale = False
          window_size = 4

In [101]: np.random.seed(42)

          counter = SpeedCounter(data_dir=os.getcwd() + '/data/',
                                 video_dir='speed_videos/',
                                 annotation_dir='speed_annotations/',
                                 lr=1e-3,
                                 batch_size=32,
                                 n_epochs=50,
                                 frame_size=128,
                                 window_size=window_size,
```

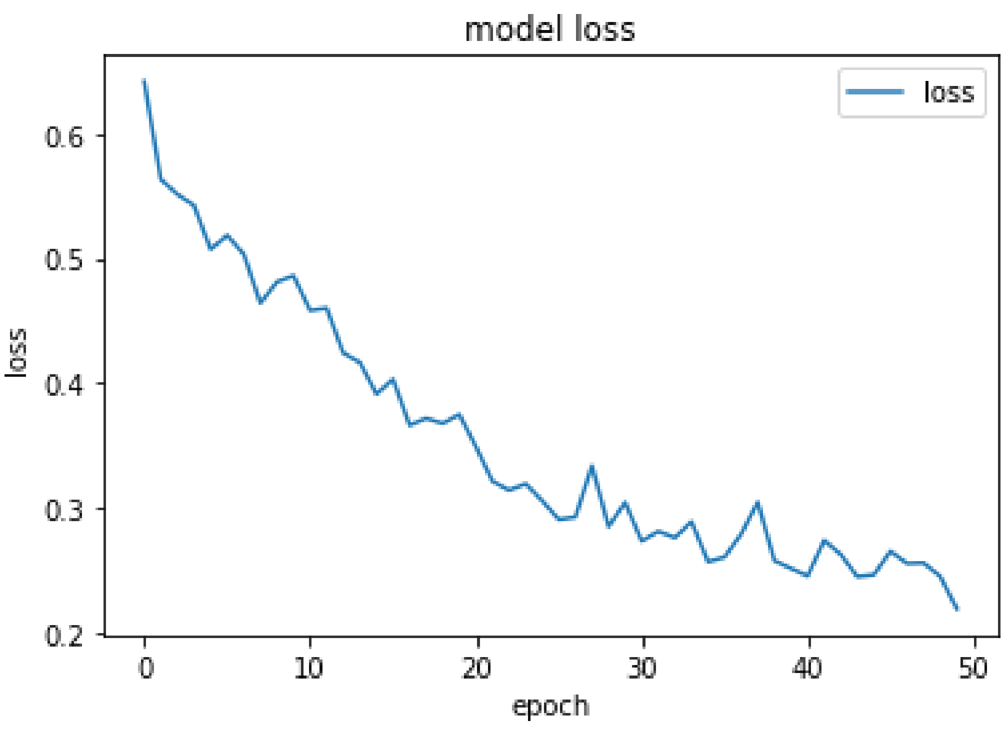
```python
                                use_flow_field=False,
                                grayscale=False,
                                verbose=False)

        # uncomment to re-train model
        #counter.train()
```

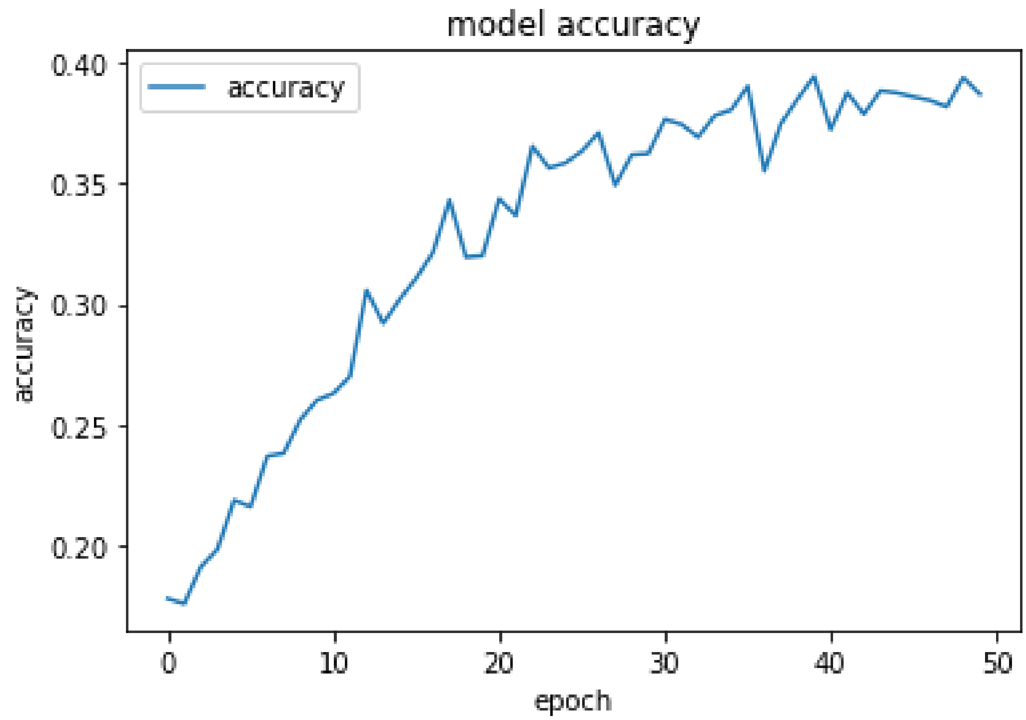
```
Total Frames: 14415
Total Samples: 3603
Model: "model_10"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
video (InputLayer)           (None, 4, 128, 128, 3)    0
_________________________________________________________________
conv3d_26 (Conv3D)           (None, 3, 113, 113, 4)    6148
_________________________________________________________________
batch_normalization_26 (Batc (None, 3, 113, 113, 4)    16
_________________________________________________________________
activation_26 (Activation)   (None, 3, 113, 113, 4)    0
_________________________________________________________________
max_pooling3d_26 (MaxPooling (None, 3, 56, 56, 4)      0
_________________________________________________________________
conv3d_27 (Conv3D)           (None, 2, 49, 49, 8)      4104
_________________________________________________________________
batch_normalization_27 (Batc (None, 2, 49, 49, 8)      32
_________________________________________________________________
activation_27 (Activation)   (None, 2, 49, 49, 8)      0
_________________________________________________________________
max_pooling3d_27 (MaxPooling (None, 2, 24, 24, 8)      0
_________________________________________________________________
conv3d_28 (Conv3D)           (None, 2, 21, 21, 16)     2064
_________________________________________________________________
batch_normalization_28 (Batc (None, 2, 21, 21, 16)     64
_________________________________________________________________
activation_28 (Activation)   (None, 2, 21, 21, 16)     0
_________________________________________________________________
max_pooling3d_28 (MaxPooling (None, 2, 10, 10, 16)     0
_________________________________________________________________
conv3d_29 (Conv3D)           (None, 2, 8, 8, 32)       4640
_________________________________________________________________
batch_normalization_29 (Batc (None, 2, 8, 8, 32)       128
_________________________________________________________________
activation_29 (Activation)   (None, 2, 8, 8, 32)       0
_________________________________________________________________
max_pooling3d_29 (MaxPooling (None, 2, 4, 4, 32)       0
_________________________________________________________________
conv3d_30 (Conv3D)           (None, 2, 2, 2, 64)       18496
```

```
_________________________________________________________________
batch_normalization_30 (Batc (None, 2, 2, 2, 64)       256
_________________________________________________________________
activation_30 (Activation)   (None, 2, 2, 2, 64)       0
_________________________________________________________________
max_pooling3d_30 (MaxPooling (None, 2, 1, 1, 64)       0
_________________________________________________________________
flatten_6 (Flatten)          (None, 128)               0
_________________________________________________________________
frames (Dense)               (None, 4)                 516
=================================================================
Total params: 36,464
Trainable params: 36,216
Non-trainable params: 248
_________________________________________________________________
None
Epoch 0 / 50
Epoch Loss: 0.642, Epoch Accuracy: 0.178
Epoch 1 / 50
Epoch Loss: 0.564, Epoch Accuracy: 0.176
Epoch 2 / 50
Epoch Loss: 0.552, Epoch Accuracy: 0.191
Epoch 3 / 50
Epoch Loss: 0.543, Epoch Accuracy: 0.198
Epoch 4 / 50
Epoch Loss: 0.507, Epoch Accuracy: 0.219
Epoch 5 / 50
Epoch Loss: 0.519, Epoch Accuracy: 0.216
Epoch 6 / 50
Epoch Loss: 0.503, Epoch Accuracy: 0.237
Epoch 7 / 50
Epoch Loss: 0.464, Epoch Accuracy: 0.238
Epoch 8 / 50
Epoch Loss: 0.481, Epoch Accuracy: 0.252
Epoch 9 / 50
Epoch Loss: 0.486, Epoch Accuracy: 0.260
Epoch 10 / 50
Epoch Loss: 0.458, Epoch Accuracy: 0.263
Epoch 11 / 50
Epoch Loss: 0.460, Epoch Accuracy: 0.270
Epoch 12 / 50
Epoch Loss: 0.424, Epoch Accuracy: 0.306
Epoch 13 / 50
Epoch Loss: 0.417, Epoch Accuracy: 0.292
Epoch 14 / 50
Epoch Loss: 0.391, Epoch Accuracy: 0.302
Epoch 15 / 50
Epoch Loss: 0.403, Epoch Accuracy: 0.311
```

```
Epoch 16 / 50
Epoch Loss: 0.366, Epoch Accuracy: 0.321
Epoch 17 / 50
Epoch Loss: 0.372, Epoch Accuracy: 0.343
Epoch 18 / 50
Epoch Loss: 0.368, Epoch Accuracy: 0.320
Epoch 19 / 50
Epoch Loss: 0.375, Epoch Accuracy: 0.320
Epoch 20 / 50
Epoch Loss: 0.349, Epoch Accuracy: 0.344
Epoch 21 / 50
Epoch Loss: 0.322, Epoch Accuracy: 0.337
Epoch 22 / 50
Epoch Loss: 0.314, Epoch Accuracy: 0.366
Epoch 23 / 50
Epoch Loss: 0.319, Epoch Accuracy: 0.357
Epoch 24 / 50
Epoch Loss: 0.306, Epoch Accuracy: 0.359
Epoch 25 / 50
Epoch Loss: 0.291, Epoch Accuracy: 0.364
Epoch 26 / 50
Epoch Loss: 0.293, Epoch Accuracy: 0.371
Epoch 27 / 50
Epoch Loss: 0.334, Epoch Accuracy: 0.349
Epoch 28 / 50
Epoch Loss: 0.285, Epoch Accuracy: 0.362
Epoch 29 / 50
Epoch Loss: 0.305, Epoch Accuracy: 0.362
Epoch 30 / 50
Epoch Loss: 0.273, Epoch Accuracy: 0.377
Epoch 31 / 50
Epoch Loss: 0.281, Epoch Accuracy: 0.375
Epoch 32 / 50
Epoch Loss: 0.276, Epoch Accuracy: 0.369
Epoch 33 / 50
Epoch Loss: 0.289, Epoch Accuracy: 0.378
Epoch 34 / 50
Epoch Loss: 0.257, Epoch Accuracy: 0.381
Epoch 35 / 50
Epoch Loss: 0.261, Epoch Accuracy: 0.391
Epoch 36 / 50
Epoch Loss: 0.279, Epoch Accuracy: 0.355
Epoch 37 / 50
Epoch Loss: 0.305, Epoch Accuracy: 0.375
Epoch 38 / 50
Epoch Loss: 0.258, Epoch Accuracy: 0.385
Epoch 39 / 50
Epoch Loss: 0.251, Epoch Accuracy: 0.394
```

```
Epoch 40 / 50
Epoch Loss: 0.245, Epoch Accuracy: 0.373
Epoch 41 / 50
Epoch Loss: 0.274, Epoch Accuracy: 0.388
Epoch 42 / 50
Epoch Loss: 0.263, Epoch Accuracy: 0.379
Epoch 43 / 50
Epoch Loss: 0.245, Epoch Accuracy: 0.389
Epoch 44 / 50
Epoch Loss: 0.246, Epoch Accuracy: 0.388
Epoch 45 / 50
Epoch Loss: 0.265, Epoch Accuracy: 0.386
Epoch 46 / 50
Epoch Loss: 0.255, Epoch Accuracy: 0.385
Epoch 47 / 50
Epoch Loss: 0.256, Epoch Accuracy: 0.382
Epoch 48 / 50
Epoch Loss: 0.245, Epoch Accuracy: 0.394
Epoch 49 / 50
Epoch Loss: 0.219, Epoch Accuracy: 0.387
```



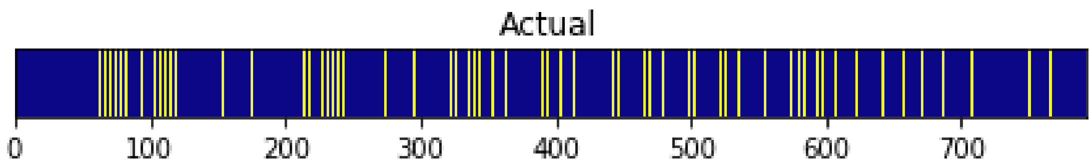



```
In [108]: model = load_model('RGB')
```

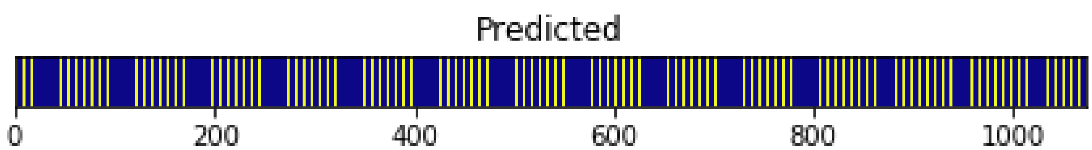
The function below opens a speed video and splits it into the *k*-frame clips and runs each clip through the model to get a prediction for which frames contain jumps. The function returns the full one-hot label of the clip and the full prediction vector for each frame from many predictions.

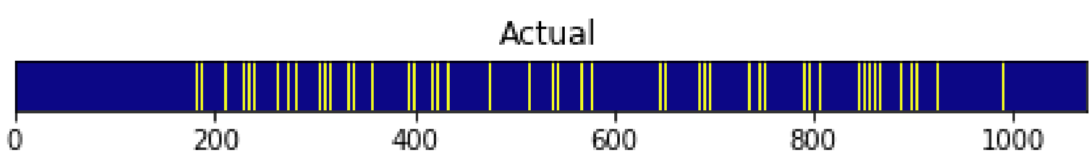
```
In [105]: for _ in range(5):
              video_path = np.random.choice(os.listdir(data_dir + video_dir))
              print(video_path)
              label, pred = count_video(video_path, threshold=0.8)
              print('Actual:', int(np.sum(label)), 'Predicted:', int(np.sum(pred)))
```

```
swe_1.mp4
```

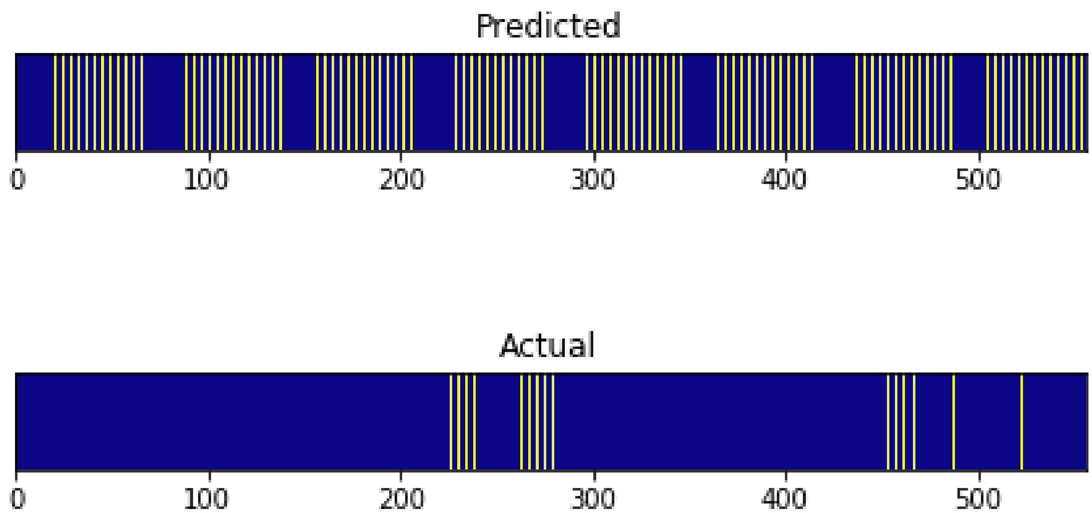



```
Actual: 124 Predicted: 197
korea_1.mp4
```

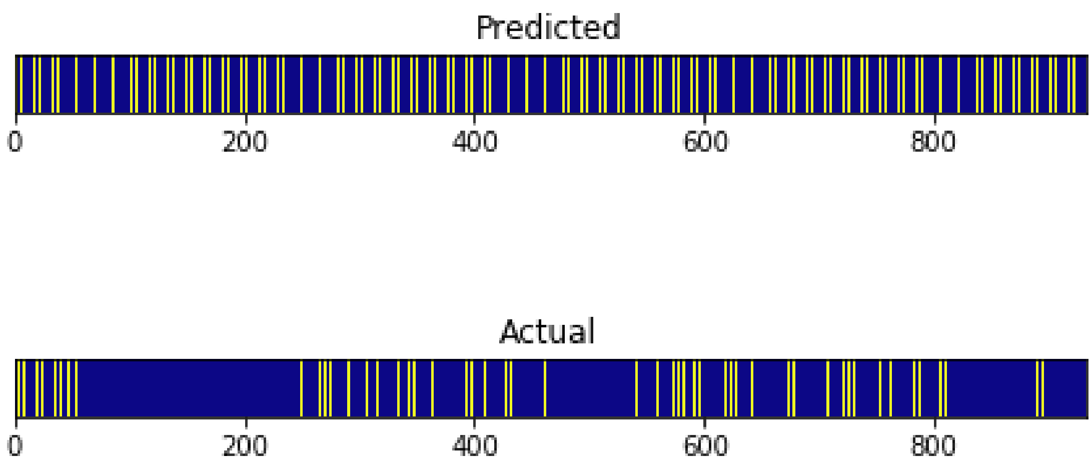




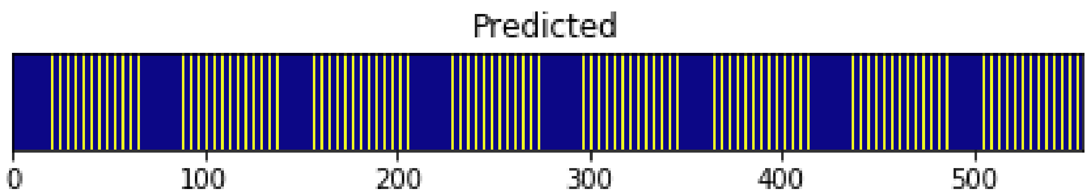

```
Actual: 136 Predicted: 268
hiro_2.mp4
```

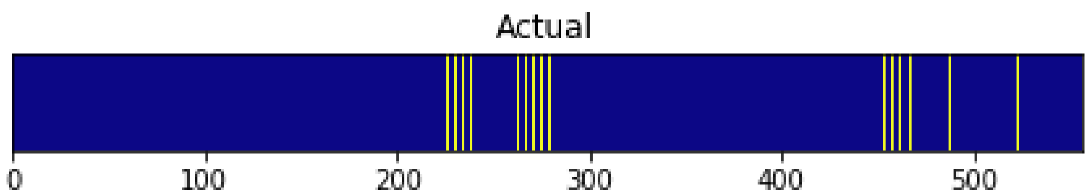



```
Actual: 28 Predicted: 139
china_1.mp4
```




```
Actual: 138 Predicted: 232
hiro_2.mp4
```






```
Actual: 28 Predicted: 139
```

The main goal of this project however, is not to develop a perfect model which can achieve 100% accuracy. The goal is to understand the inner workings of this particular method. One way to do this is to visualize the intermediate activations of each 3D convolutional filter.

The function below creates a new model which outputs the activation of each convolution layer:

Let's try it out on one of the videos from our dataset:

```
In [114]: video_path = 'hiro_1.mp4'
          print(video_path)
          clip, y = get_clip_and_label(video_path)
```

```
hiro_1.mp4
```

```
In [115]: interactive_plot = interactive(plot_frame(clip, y), i=(0, window_size - 2))
          output = interactive_plot.children[-1]
          output.layout.height = '360px'
          interactive_plot
```

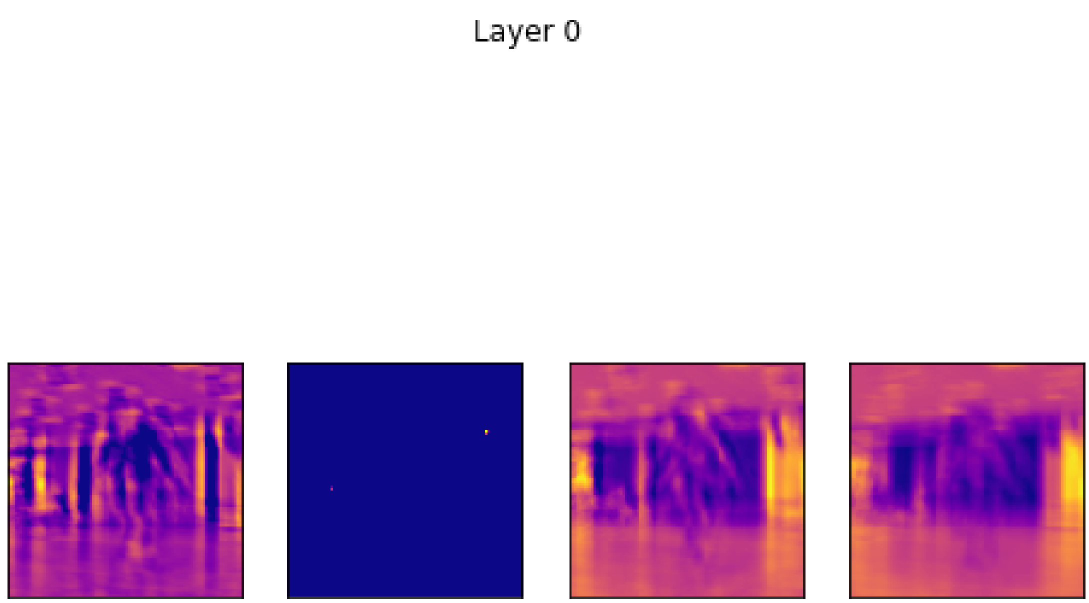
```
interactive(children=(IntSlider(value=1, description='i', max=2), Output(layout=Layout(height=
```

```
In [108]: activations = get_model_activations(clip)
```

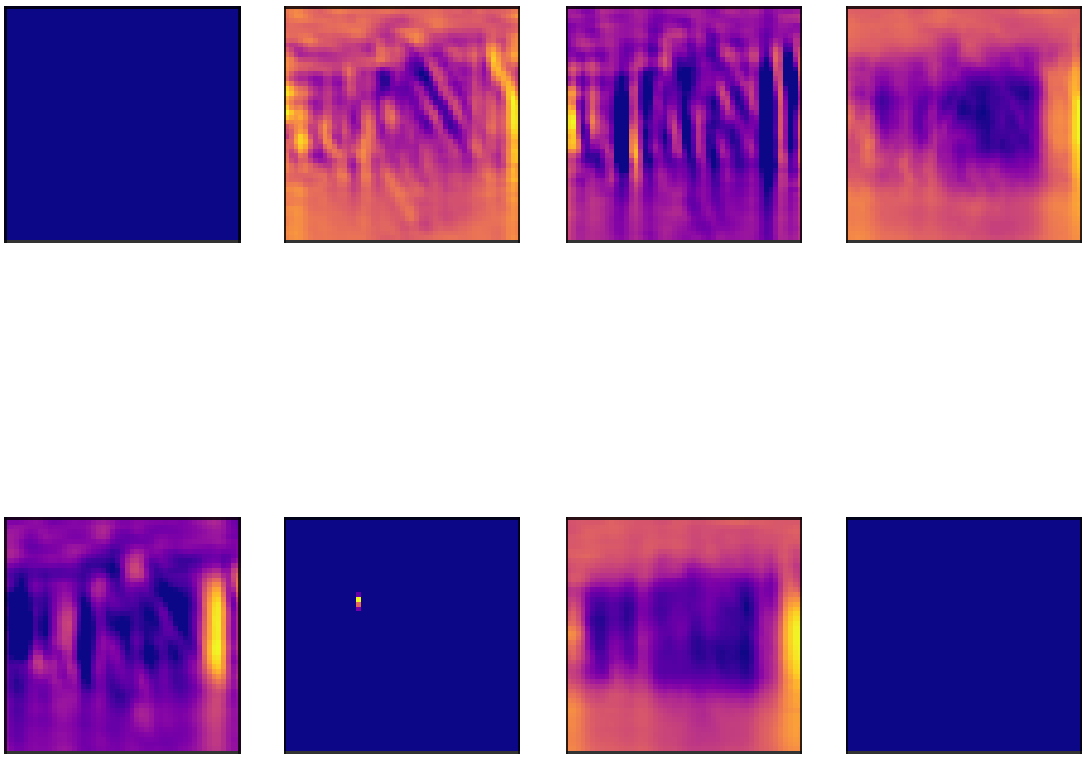
One main downside to this method is that beyond the first layer, all activations only have 1 'frame' (i.e their 3rd time axis is flattened after the first two convolutions)

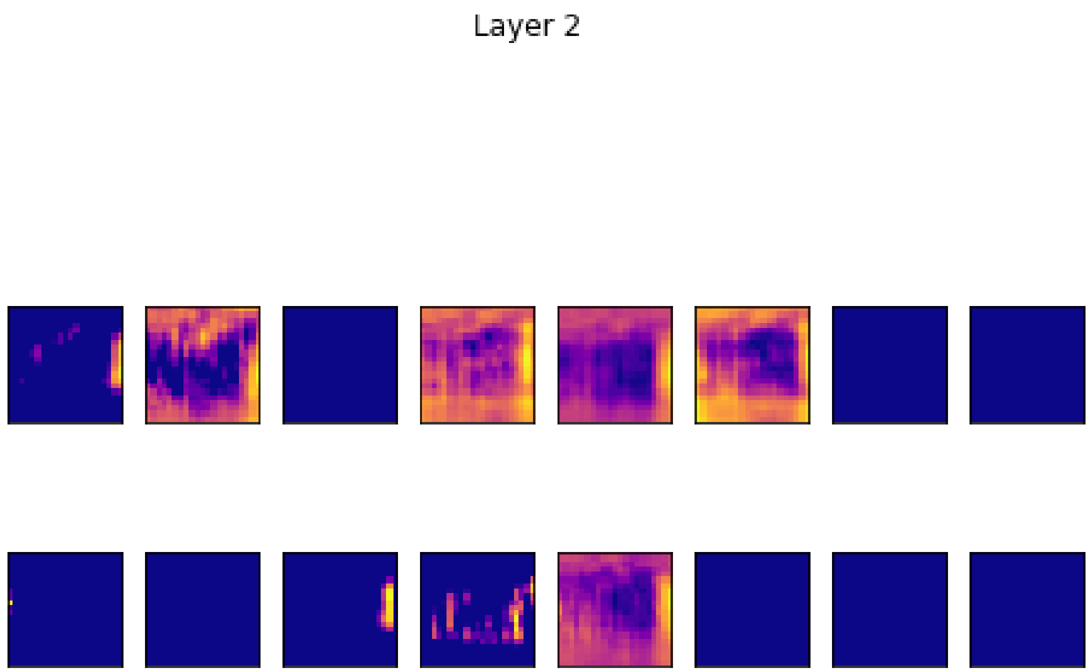
```
In [109]: import math

          fig = plt.figure(figsize=(8, 8))
          for i in range(len(activations)):
              fig = plt.figure(figsize=(8, 8))
              fig.suptitle('Layer %d' % i)
              num_filters = activations[i].shape[-1]
              rows = math.sqrt(num_filters)
              cols = num_filters // rows * 2
              for j in range(activations[i].shape[-1]):
                  ax = plt.subplot(rows, cols, j + 1)
                  ax.set_xticks([])
                  ax.set_yticks([])
                  ax.imshow(activations[i][0, 0, ..., j], cmap='plasma')
              plt.subplots_adjust(top=0.8)
              plt.show()
```

```
<Figure size 576x576 with 0 Axes>
```

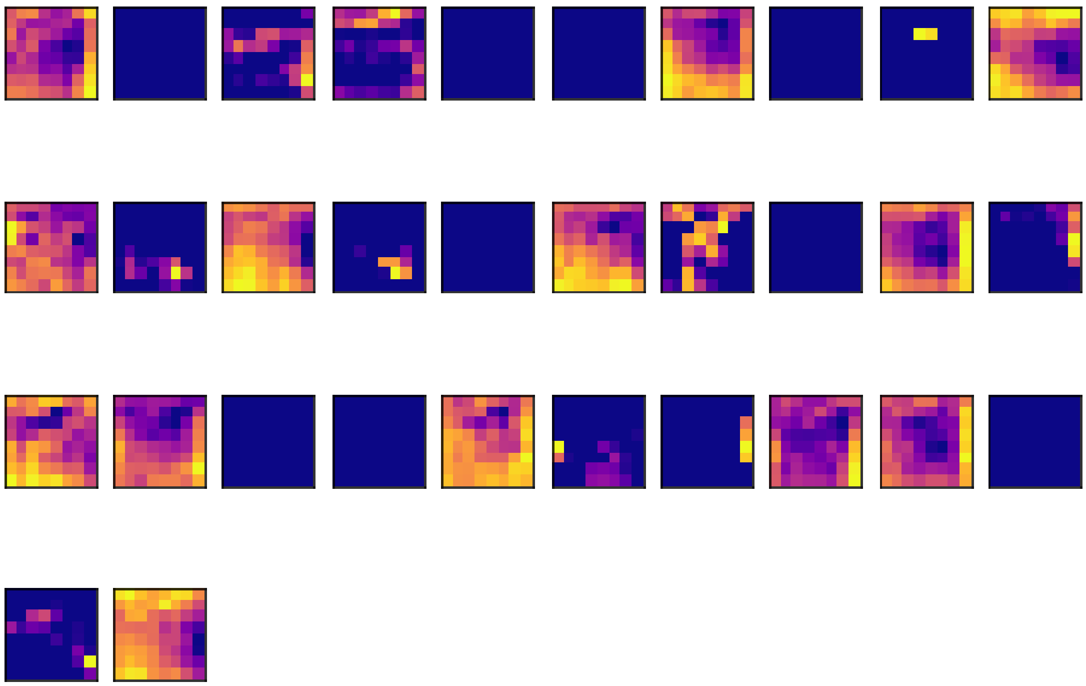


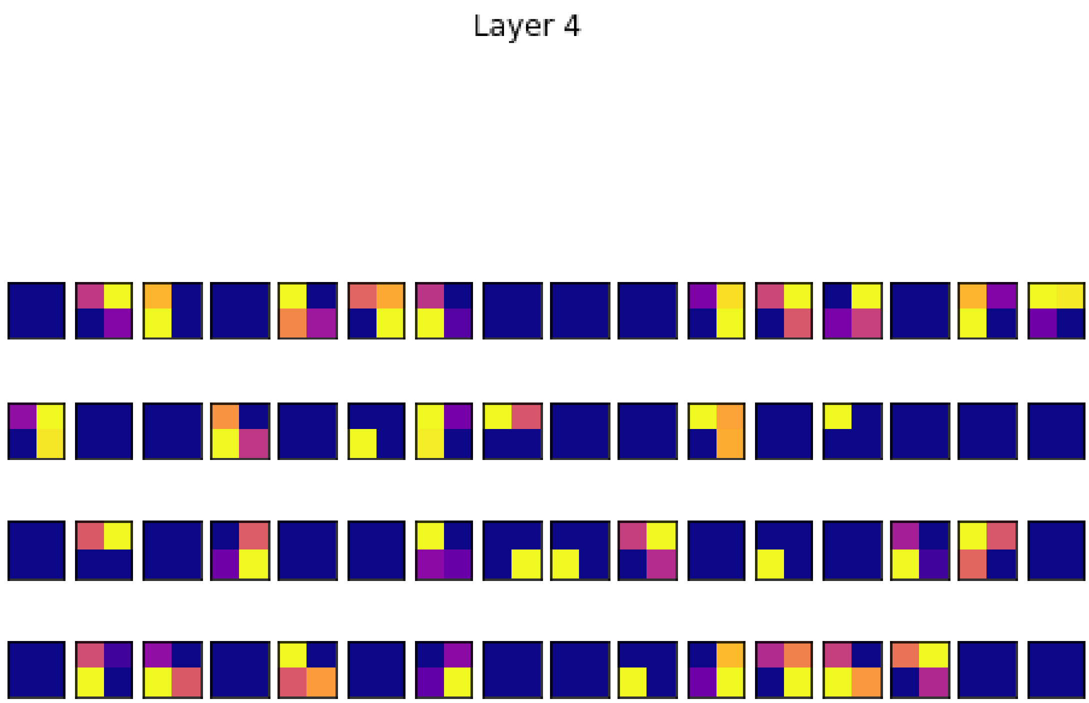
Layer 1




Layer 2

Layer 3





These activations look alsmost identical to the grayscale model activation visualizations.

```
In [116]: layer_dict = dict([(layer.name, layer) for layer in model.layers])
          print(layer_dict.keys())
```

```
dict_keys(['conv3d_30', 'batch_normalization_30', 'max_pooling3d_27', 'activation_30', 'activa
```

```
In [117]: rgb_filter_images = []
          layer_names = []

          for layer in layer_dict.keys():
              if 'activation' in layer:
                  try:
                      layer_names.append(layer)
                      visualizations = plot_conv_layer(model, layer, layer_dict, vis_iter=15)
                      rgb_filter_images.append(visualizations)
                  except Exception as e:
                      print(e)
                      pass
```

```
1 / 9
2 / 9
3 / 9
4 / 9
```

```
5 / 9
6 / 9
7 / 9
8 / 9
9 / 9
1 / 9
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9 / 9
1 / 9
2 / 9
3 / 9
4 / 9
5 / 9
6 / 9
7 / 9
8 / 9
9 / 9
```

In [120]:
```
vis_i = 0
interactive_plot = interactive(plot_filters(rgb_filter_images[vis_i], layer_names[vis
output = interactive_plot.children[-1]
output.layout.height = '480px'
vis_i += 1
```

```
interactive_plot
```

```
interactive(children=(IntSlider(value=1, description='i', max=3), Output(layout=Layout(height=
```

```
In [121]: interactive_plot = interactive(plot_filters(rgb_filter_images[vis_i], layer_names[vi
          output = interactive_plot.children[-1]
          output.layout.height = '480px'
          vis_i += 1
          interactive_plot
```

```
interactive(children=(IntSlider(value=1, description='i', max=3), Output(layout=Layout(height=
```

```
In [122]: interactive_plot = interactive(plot_filters(rgb_filter_images[vis_i], layer_names[vi
          output = interactive_plot.children[-1]
          output.layout.height = '480px'
          vis_i += 1
          interactive_plot
```

```
interactive(children=(IntSlider(value=1, description='i', max=3), Output(layout=Layout(height=
```

```
In [123]: interactive_plot = interactive(plot_filters(rgb_filter_images[vis_i], layer_names[vi
          output = interactive_plot.children[-1]
          output.layout.height = '480px'
          vis_i += 1
          interactive_plot
```

```
interactive(children=(IntSlider(value=1, description='i', max=3), Output(layout=Layout(height=
```

```
In [124]: interactive_plot = interactive(plot_filters(rgb_filter_images[vis_i], layer_names[vi
          output = interactive_plot.children[-1]
          output.layout.height = '480px'
          vis_i += 1
          interactive_plot
```

```
interactive(children=(IntSlider(value=1, description='i', max=3), Output(layout=Layout(height=
```

```
In [12]: %%HTML
         <img src="figures/filters/rgb/activation_26.gif" width="360" height="360" />
```

```
<IPython.core.display.HTML object>
```

```
In [13]: %%HTML
         <img src="figures/filters/rgb/activation_27.gif" width="360" height="360" />
```

```
<IPython.core.display.HTML object>
```

```
In [14]: %%HTML
         <img src="figures/filters/rgb/activation_28.gif" width="360" height="360" />
```

```
<IPython.core.display.HTML object>
```

```
In [15]: %%HTML
         <img src="figures/filters/rgb/activation_29.gif" width="360" height="360" />
```

```
<IPython.core.display.HTML object>
```

```
In [16]: %%HTML
         <img src="figures/filters/rgb/activation_30.gif" width="360" height="360" />
```

```
<IPython.core.display.HTML object>
```

Once again, these visualizations looks very similar to the grayscale visualizations except in the deeper layers. The model seemd to be picking up on the rapidly changing motion that occurs at the jumper's feet during a jump, but this is not as pronounced as in the grayscale model. Based on the lack on increased performance from the grayscale model to this, I think it is sufficient to only use grayscale values and not the full RGB spectrum of the video.

Overall, this project was a great dive into the inner workings of neural networks and how to approach certain vision problems from a computational perspective. Even though the models are not yet at the level of human judges, I think in the future it will be possible to collect more data a train a more general model. Until then, we can use this smaller dataset and model to learn about which features give rise to better performance and how to better adjust out model architecture and training.