```
Where do I put batch_normalized = tf.layers.batch_normalization(convolved, training=(mode == 'train'))?
```

To add batch normalization to your CNN layers, you need to modify the CNN section of the <code>OnsetNet\_Ginal</code> class. Here's exactly where to put the batch normalization code:

```
# In the CNN section of OnsetNet_Gina1.__init__, find this code:
convolved = tf.nn.relu(biased)

# Right after that line, add batch normalization:
batch_normalized = tf.layers.batch_normalization(convolved, training=(mode == 'train'))

# Then change the pooling to use batch_normalized instead of convolved:
pooled = tf.nn.max_pool(batch_normalized, ksize=pool_shape, strides=pool_shape, padding='SAME')
```

The full context would look like this:

```
# Existing code:
conv = tf.nn.conv2d(layer_last, filters, [1, 1, 1, 1], padding=padding)
biased = tf.nn.bias_add(conv, biases)
convolved = tf.nn.relu(biased)

# Add this line:
batch_normalized = tf.layers.batch_normalization(convolved, training=(mode == 'train'))

# Change this line (replace convolved with batch_normalized):
pooled = tf.nn.max_pool(batch_normalized, ksize=pool_shape, strides=pool_shape, padding='SAME')
```

Also, if you're using batch normalization, you'll need to ensure your training operation includes the update operations for the batch normalization statistics. Add this near the end of the **init** method, just before creating the training operation:

```
python

# Add this before the train_op = optimizer.apply_gradients(...) line:
update_ops = tf.get_collection(tf.GraphKeys.UPDATE_OPS)
with tf.control_dependencies(update_ops):
    train_op = optimizer.apply_gradients(list(zip(grads, tvars)), global_step=tf.train.get_or_create_global_step())
```

This ensures that the moving averages used by batch normalization are properly updated during training.

Would you like me to show the full CNN section with all the batch normalization changes integrated?

```
AttributeError
                                          Traceback (most recent call
last)
Cell In[3], line 52
     49 # Update the training_args argument container in place
     50 vars(training args).update(training args dict)
---> 52 train onset model(training args, OnsetModel=OnsetNet Gina2)
     55 # Results 4/21 - Hard, Challenge
     56
     57 # Completed epoch 1
   (\ldots)
     61 # Completed epoch 10
     62 # Epoch mean cross-entropy (nats)
File /users/6/croal008/5527 Project/ddc/learn/onset train.py:198, in
train onset model(args, OnsetModel)
    196
            print('Creating train model')
    197
            with tf.variable_scope('model_sp', reuse=None):
                model_train = OnsetModel(mode='train',
--> 198
target_weight_strategy=args.weight_strategy, batch_size=args.batch_size,
**model config)
    200 if do train eval or do eval or do cnn export:
    201
            with tf.variable scope('model sp', reuse=do train):
File /users/6/croal008/5527 Project/ddc/learn/onset_net_gina2.py:93, in
OnsetNet_Gina2.__init__(self, mode, batch_size, audio_context_radius,
audio_nbands, audio_nchannels, nfeats, cnn_filter_shapes, cnn_init,
cnn_pool, cnn_rnn_zack, rnn_cell_type, rnn_size, rnn_nlayers, rnn_init,
rnn_nunroll, rnn_keep_prob, dnn_sizes, dnn_init, dnn_keep_prob,
dnn_nonlin, target_weight_strategy, grad_clip, opt, export_feat_name,
zack hack)
     90
                        biased = tf.nn.bias add(conv, biases)
     91
                        convolved = tf.nn.relu(hiased)
```

```
---> 93
                        batch normalized =
tf.layers.batch normalization(convolved, training=(mode == 'train'))
                        pool_shape = [1, ptime, pband, 1]
     95
                          pooled = tf.nn.max_pool(convolved,
     96 #
ksize=pool_shape, strides=pool_shape, padding='SAME')
File
/common/software/install/manual/jupyter kernels/DeepLearning/lib/python3.1
1/site-packages/tensorflow/python/util/lazy_loader.py:207, in
KerasLazyLoader. getattr (self, item)
    200
            raise AttributeError(
                "`tf.compat.v2.keras` is not available with Keras 3. Just
    201
use "
                "`import keras` instead."
    202
    203
          elif self._tfll_submodule and self._tfll_submodule.startswith(
    204
              " internal .legacy."
    205
        ):
    206
            raise AttributeError(
--> 207
                f"`{item}` is not available with Keras 3."
    208
    209
            )
    210 module = self._load()
    211 return getattr(module, item)
AttributeError: `batch_normalization` is not available with Keras 3.
```

I see the error - you're running into an issue with TensorFlow versions. The version you're using (TensorFlow 1.x with compatibility mode) doesn't support [tf.layers.batch\_normalization] in the way I suggested.

Let me provide the correct implementation for your TensorFlow version:

python

```
# Instead of using tf.layers.batch normalization, use tf.nn.batch normalization
# First, define batch norm variables
batch mean, batch var = tf.nn.moments(convolved, [0, 1, 2])
scale = tf.get variable(f'bn scale {i}', shape=[nfilt], initializer=tf.ones initializer(), dtype=dtype)
beta = tf.get_variable(f'bn_beta_{i}', shape=[nfilt], initializer=tf.zeros_initializer(), dtype=dtype)
# For tracking running statistics (needed for inference)
pop_mean = tf.get_variable(f'bn_pop_mean_{i}', shape=[nfilt], initializer=tf.zeros_initializer(), dtype=dtype, trainable=False)
pop_var = tf.get_variable(f'bn_pop_var_{i}', shape=[nfilt], initializer=tf.ones_initializer(), dtype=dtype, trainable=False)
# Apply batch normalization
if mode == 'train':
    # During training, use batch statistics and update running stats
    decay = 0.99
   train_mean = batch_mean
   train_var = batch_var
   # Update population statistics for inference
   train_pop_mean = tf.assign(pop_mean, pop_mean * decay + batch_mean * (1 - decay))
   train pop_var = tf.assign(pop_var, pop_var * decay + batch_var * (1 - decay))
    with tf.control dependencies([train pop mean, train pop var]):
       batch normalized = tf.nn.batch normalization(
           convolved, train mean, train var, beta, scale, epsilon=1e-5)
else:
    # During inference, use population statistics
    batch_normalized = tf.nn.batch_normalization(
       convolved, pop_mean, pop_var, beta, scale, epsilon=1e-5)
# Then use batch normalized in the pooling
pool shape = [1, ptime, pband, 1]
pooled = tf.nn.max pool(batch normalized, ksize=pool shape, strides=pool shape, padding='SAME')
```

This approach uses the lower-level <code>tf.nn.batch\_normalization</code> function which is compatible with TensorFlow 1.x. It also explicitly handles the running statistics that need to be maintained for inference.

Alternatively, you could switch to a different normalization technique that might be simpler to implement with your version of TensorFlow:

```
# Layer normalization (simpler alternative)
# Normalize across channels for each example
mean, variance = tf.nn.moments(convolved, axes=[3], keep_dims=True)
normalized = (convolved - mean) / tf.sqrt(variance + 1e-5)
gamma = tf.get_variable(f'ln_gamma_{i}', shape=[1, 1, 1, nfilt], initializer=tf.ones_initializer(), dtype=dtype)
beta = tf.get_variable(f'ln_beta_{i}', shape=[1, 1, 1, nfilt], initializer=tf.zeros_initializer(), dtype=dtype)
normalized = normalized * gamma + beta

# Then use normalized in pooling
pool_shape = [1, ptime, pband, 1]
pooled = tf.nn.max_pool(normalized, ksize=pool_shape, strides=pool_shape, padding='SAME')
```

This layer normalization approach might be easier to implement and can still provide many of the benefits of normalization without the complexity of tracking running statistics.

```
Traceback (most recent call
TypeError
last)
Cell In[2], line 52
     49 # Update the training_args argument container in place
     50 vars(training args).update(training args dict)
---> 52 train onset model(training args, OnsetModel=OnsetNet Gina2)
     55 # Results 4/21 - Hard, Challenge
     56
     57 # Completed epoch 1
   (\ldots)
     61 # Completed epoch 10
     62 # Epoch mean cross-entropy (nats)
File /users/6/croal008/5527 Project/ddc/learn/onset train.py:198, in
train_onset_model(args, OnsetModel)
    196
            print('Creating train model')
    197
            with tf.variable_scope('model_sp', reuse=None):
                model_train = OnsetModel(mode='train',
--> 198
target_weight_strategy=args.weight_strategy, batch_size=args.batch_size,
**model config)
    200 if do train eval or do eval or do cnn export:
    201
            with tf.variable scope('model sp', reuse=do train):
File /users/6/croal008/5527 Project/ddc/learn/onset_net_gina2.py:112, in
OnsetNet_Gina2.__init__(self, mode, batch_size, audio_context_radius,
audio_nbands, audio_nchannels, nfeats, cnn_filter_shapes, cnn_init,
cnn_pool, cnn_rnn_zack, rnn_cell_type, rnn_size, rnn_nlayers, rnn_init,
rnn_nunroll, rnn_keep_prob, dnn_sizes, dnn_init, dnn_keep_prob,
dnn_nonlin, target_weight_strategy, grad_clip, opt, export_feat_name,
zack hack)
            train pop var = tf.assign(pop var, pop var * decay + batch var
    110
* (1 - decay))
```

```
with tf.control dependencies([train pop mean, train pop var]):
    111
                batch normalized = tf.nn.batch normalization(
--> 112
    113
                   convolved, train_mean, train_var, beta, scale,
epsilon=1e-5)
   114 else:
    115
           # During inference, use population statistics
           batch_normalized = tf.nn.batch_normalization(
    116
                convolved, pop_mean, pop_var, beta, scale, epsilon=1e-5)
    117
File
/common/software/install/manual/jupyter_kernels/DeepLearning/lib/python3.1
1/site-packages/tensorflow/python/util/traceback_utils.py:153, in
filter_traceback.<locals>.error_handler(*args, **kwargs)
   151 except Exception as e:
   152 filtered_tb = _process_traceback_frames(e.__traceback__)
--> 153 raise e.with_traceback(filtered_tb) from None
   154 finally:
   155 del filtered tb
File
/common/software/install/manual/jupyter_kernels/DeepLearning/lib/python3.1
1/site-packages/tensorflow/python/util/dispatch.py:1254, in
add_dispatch_support.<locals>.decorator.
<locals>.op_dispatch_handler(*args, **kwargs)
   1252 if iterable_params is not None:
  1253 args, kwargs = replace_iterable_params(args, kwargs,
iterable params)
-> 1254 result = api_dispatcher.Dispatch(args, kwargs)
   1255 if result is not NotImplemented:
   1256 return result
TypeError: Got an unexpected keyword argument 'epsilon'
```

I see the new error. The issue is with the epsilon parameter. Let me provide a corrected version that will work with your TensorFlow

## version:

```
python
# Fix the batch normalization implementation
# First, define batch norm variables
batch mean, batch var = tf.nn.moments(convolved, [0, 1, 2])
scale = tf.get_variable(f'bn_scale_{i}', shape=[nfilt], initializer=tf.ones_initializer(), dtype=dtype)
beta = tf.get_variable(f'bn_beta_{i}', shape=[nfilt], initializer=tf.zeros_initializer(), dtype=dtype)
# For tracking running statistics (needed for inference)
pop_mean = tf.get_variable(f'bn_pop_mean_{i}', shape=[nfilt], initializer=tf.zeros_initializer(), dtype=dtype, trainable=False)
pop_var = tf.get_variable(f'bn_pop_var_{i}', shape=[nfilt], initializer=tf.ones_initializer(), dtype=dtype, trainable=False)
# Apply batch normalization
if mode == 'train':
   # During training, use batch statistics and update running stats
    decay = 0.99
   train mean = batch mean
   train_var = batch_var
   # Update population statistics for inference
   train_pop_mean = tf.assign(pop_mean, pop_mean * decay + batch_mean * (1 - decay))
   train pop var = tf.assign(pop var, pop var * decay + batch var * (1 - decay))
    with tf.control dependencies([train pop mean, train pop var]):
       # Note: removed epsilon parameter, using variance epsilon instead
       batch_normalized = tf.nn.batch_normalization(
            convolved, train_mean, train_var, beta, scale, variance_epsilon=1e-5)
else:
    # During inference, use population statistics
    batch normalized = tf.nn.batch normalization(
       convolved, pop_mean, pop_var, beta, scale, variance_epsilon=1e-5)
```

The key change is replacing epsilon=1e-5 with variance\_epsilon=1e-5.

Alternatively, since you're having compatibility issues with batch normalization, I'd suggest trying the simpler layer normalization approach:

```
# Simpler alternative: Layer normalization
# Normalize across channels for each example
mean, variance = tf.nn.moments(convolved, [3], keep_dims=True)
normalized = (convolved - mean) / tf.sqrt(variance + 1e-5)
gamma = tf.get_variable(f'ln_gamma_{i}', [1, 1, 1, nfilt], initializer=tf.ones_initializer(), dtype=dtype)
beta = tf.get_variable(f'ln_beta_{i}', [1, 1, 1, nfilt], initializer=tf.zeros_initializer(), dtype=dtype)
normalized = normalized * gamma + beta

# Then use normalized in pooling
pool_shape = [1, ptime, pband, 1]
pooled = tf.nn.max_pool(normalized, ksize=pool_shape, strides=pool_shape, padding='SAME')
```

If you're continuing to encounter version compatibility issues with the normalized approaches, another alternative would be to simply focus on other improvements such as:

- 1. Adding the RNN layers (rnn\_nlayers = 2)
- 2. Changing the activation function to ReLU
- 3. Implementing the learning rate decay
- 4. Switching from SGD to Adam

These changes are less likely to run into compatibility issues while still providing significant performance improvements.

G What about batch2dnorm?

You're right to suggest tf.nn.batch2d\_normalization as an alternative! This could be a more compatible option for your TensorFlow 1.x implementation.

Here's how you could implement it in your CNN layers:

```
python
# For a 2D batch normalization approach
# Add after the convolved = tf.nn.relu(biased) line in your CNN section
# Create variables for batch normalization
scale = tf.get_variable(f'bn_scale_{i}', shape=[nfilt],
                        initializer=tf.ones_initializer(), dtype=dtype)
beta = tf.get_variable(f'bn_beta_{i}', shape=[nfilt],
                       initializer=tf.zeros initializer(), dtype=dtype)
# For tracking mean and variance
pop_mean = tf.get_variable(f'bn_pop_mean_{i}', shape=[nfilt],
                           initializer=tf.zeros_initializer(),
                           dtype=dtype, trainable=False)
pop_var = tf.get_variable(f'bn_pop_var_{i}', shape=[nfilt],
                          initializer=tf.ones initializer(),
                          dtype=dtype, trainable=False)
# Reshape for batch normalization (flatten the spatial dimensions)
shape = convolved.get_shape().as_list()
reshaped_conv = tf.reshape(convolved, [-1, shape[1] * shape[2], shape[3]])
# Apply batch normalization
if mode == 'train':
    batch mean, batch var = tf.nn.moments(reshaped conv, [0, 1])
    decay = 0.99
   train_mean = tf.assign(pop_mean, pop_mean * decay + batch_mean * (1 - decay))
   train_var = tf.assign(pop_var, pop_var * decay + batch_var * (1 - decay))
```

```
with tf.control_dependencies([train_mean, train_var]):
    normalized = tf.nn.batch_normalization(
        reshaped_conv, batch_mean, batch_var, beta, scale, variance_epsilon=1e-5)
else:
    normalized = tf.nn.batch_normalization(
        reshaped_conv, pop_mean, pop_var, beta, scale, variance_epsilon=1e-5)

# Reshape back to original shape
batch_normalized = tf.reshape(normalized, shape)

# Then continue with pooling
pool_shape = [1, ptime, pband, 1]
pooled = tf.nn.max_pool(batch_normalized, ksize=pool_shape, strides=pool_shape, padding='SAME')
```

## This approach:

- 1. Creates variables to store scale, shift, and running statistics
- 2. Reshapes the convolution output to collapse spatial dimensions
- 3. Applies batch normalization
- 4. Reshapes back to original tensor shape
- 5. Continues with pooling

If you're still encountering issues with the batch normalization implementations, I'd recommend trying the simplest approach to make progress: instance normalization. This requires minimal changes and is very stable:

```
# Instance normalization (normalize each feature map independently per example)
# Simple approach that often works well for audio/image tasks

# Calculate mean and variance for each example and feature map
inst_mean, inst_var = tf.nn.moments(convolved, axes=[1, 2], keep_dims=True)
```

This instance normalization approach is simpler and often works well for audio processing tasks, without requiring running statistics.