

# Tensor Notes

Andrew H. Fagg

Symbiotic Computing Laboratory  
University of Oklahoma

# Tensorflow Tensors

Two types:

- Symbolic tensors:
  - Contain some shape information, as well as dtype
  - Used to connect data flow graphs together
- Eager tensors:
  - Well-defined mathematical tensors
  - Shape, dtype and values

# Keras Tensors

- All are symbolic tensors
- Keras libraries (Layers, Models, ...) operate on these tensors (but in some cases can also work with symbolic TF tensors)

# Execution Modes

Eager mode:

- Tensors are always Eager tensors
- Code is procedural: executes immediately (so, more intuitive from a programming language point of view)
- Helpful for interactive debugging

# Symbolic Tensor Mode

- The code produces a data-flow graph
- This code works in terms of non-Eager tensors
- Methods including `model.fit()` `.predict()` `.evaluate()`
  - Push Eager tensors through the data-flow graph

# Eager vs Symbolic Tensors

- Keras classes: (essentially) always non-Eager
- Tensorflow classes: mix of eager and non-Eager operators  
(some operators will work with either)

# Loss Functions

- Translate a set of examples (input/desired output pairs) into 'loss'
- `model.fit()`, `.evaluate()` will accumulate the data across the set of batches to compute the scalar loss
- Ultimately, loss functions are evaluated with Eager tensors, but often use in graph mode
  - Requires bridging the gap between symbolic and Eager tensors

# Loss Example

```
@classmethod  
  
def mdn_loss(cls, y, dist):  
  
    return -dist.log_prob(y)
```

- Referenced in the compile step
- Computes loss for each example individually
- Expressed using Eager tensors
- `compile()` adds a wrapper that connects this loss into the symbolic graph that is being created



# Keras Loss Example

Relationship of symbolic and Eager tensors is more explicit:

```
class WeightedLogLikelihood(Loss):
    def __init__(self, name="weighted_log_likelihood"):
        super().__init__(name=name)

    def call(self, y_true, y_pred, sample_weight=None):
        n_log_prob = -y_pred.log_prob(y_true)

        if sample_weight is not None:
            log_prob *= sample_weight
            loss = tf.reduce_sum(n_log_prob) / tf.reduce_sum(sample_weight)
        else:
            loss = tf.reduce_mean(n_log_prob)

    return loss
```

# Metrics

- Applied to the entirety of a data set
- ... even when that data set is composed of multiple batches
- For custom metrics, must provide methods for:
  - Accumulating the needed data across batches
  - Generating the output metric given the accumulated data
  - Resetting the accumulators

# Metric Example

```
class CustomMSE(Metric):
    def __init__(self, name="custom_mse", **kwargs):
        super().__init__(name=name, **kwargs)
        # Variables for holding the accumulated values (numerator and denominator)
        self.total = self.add_weight(name="total", initializer="zeros")
        self.count = self.add_weight(name="count", initializer="zeros")

    def update_state(self, y_true, y_pred, sample_weight=None):
        # One batch
        error = tf.square(y_true - y_pred)
        if sample_weight is not None:
            error *= tf.cast(sample_weight, error.dtype)
        self.total.assign_add(tf.reduce_sum(error))
        self.count.assign_add(tf.cast(tf.size(y_true), tf.float32))

    def result(self):
        return self.total / self.count

    def reset_state(self):
        self.total.assign(0.0)
        self.count.assign(0.0)
```