Midterm Presentation：Image Classification based on CNN

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Outline

- Architecture
- CNN Algorithm
- Experiments
- Team Coordiation
- Furture work

Progress

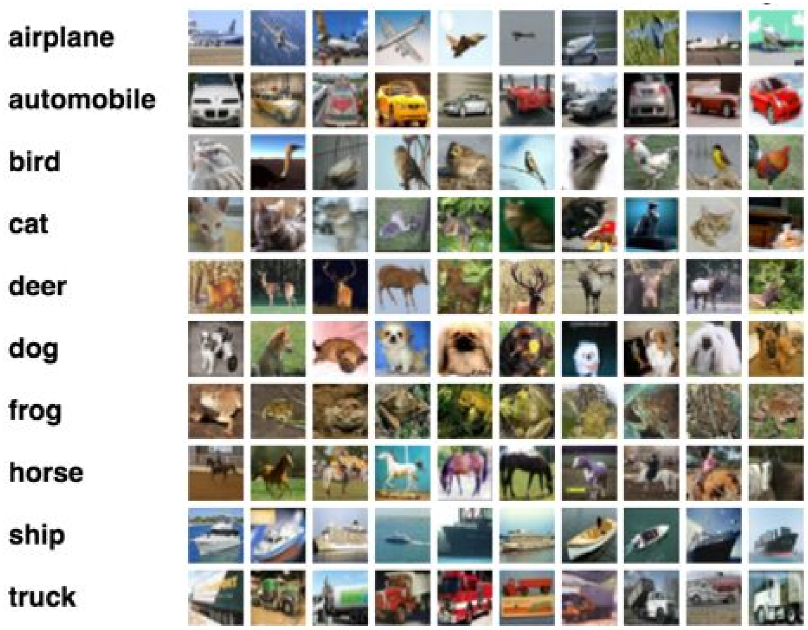
- Learn the neural network model.
- Learn the TensorFlow structure.
- Train CIFAR-10 example in TensorFlow.
- Change different CPU / GPU combinations to find the best arrangement.
- Adjust structure and parameters of CNN for CIFAR-10

Basic Component

TensorFlow: An open source machine learning framework.

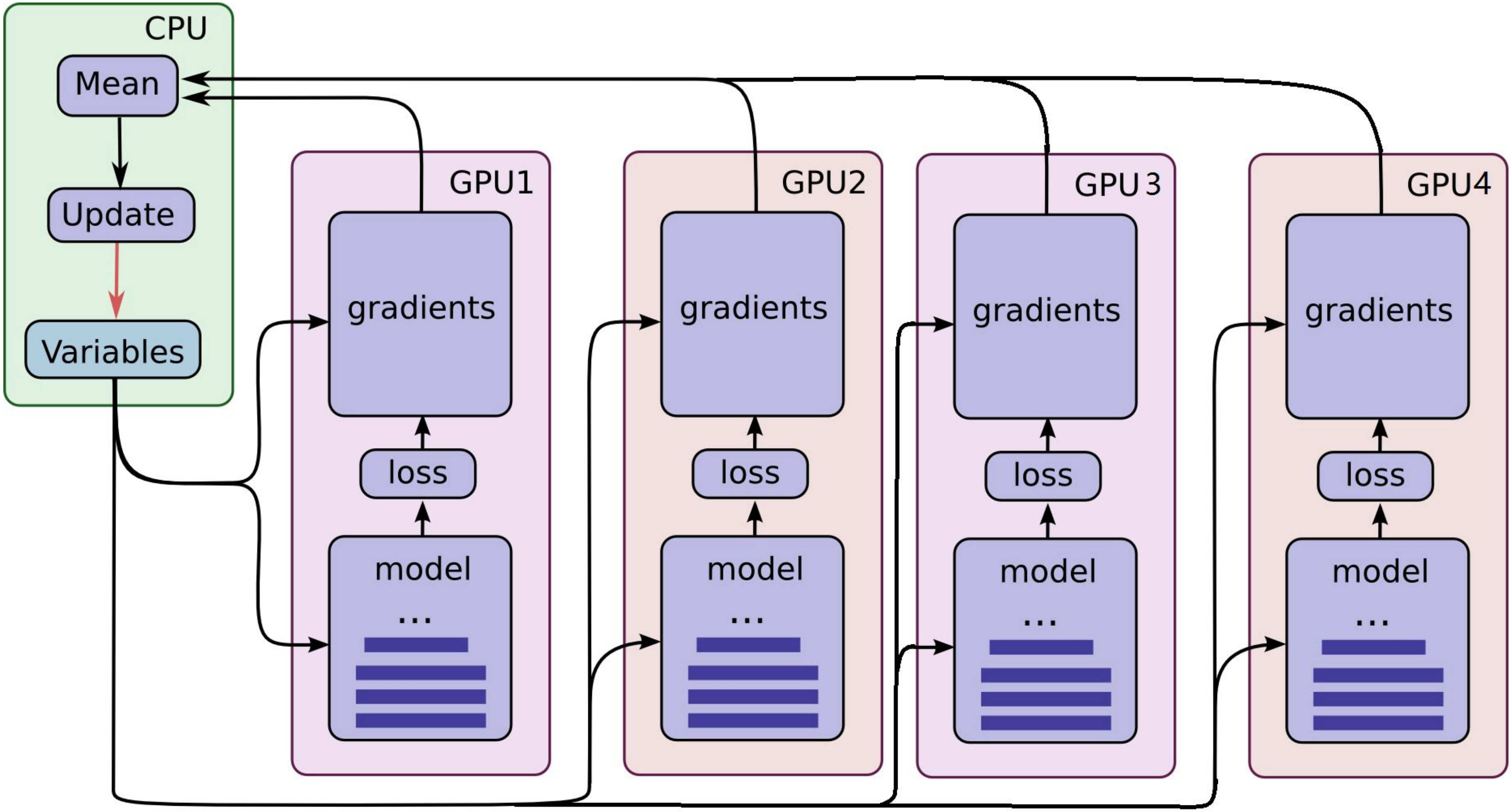
GPU / CPU: Parallelized computing platform.

CIFAR10: A smaller dataset compare to ImageNet.

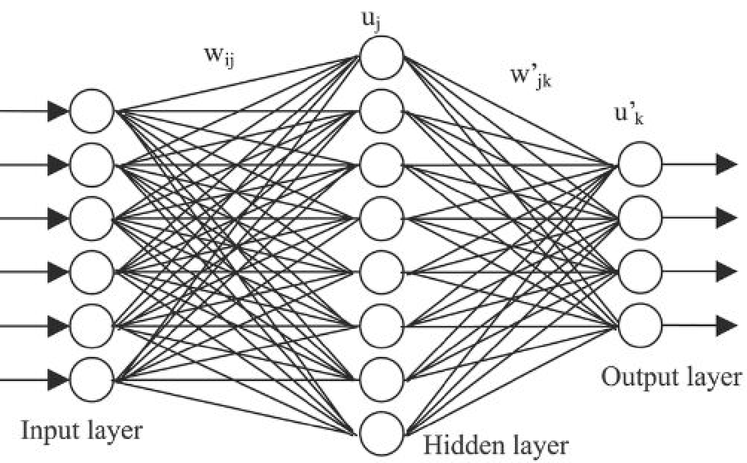


Consists of 60000 32x32 colour images in 10 classes.

Multiple GPUs Architecture

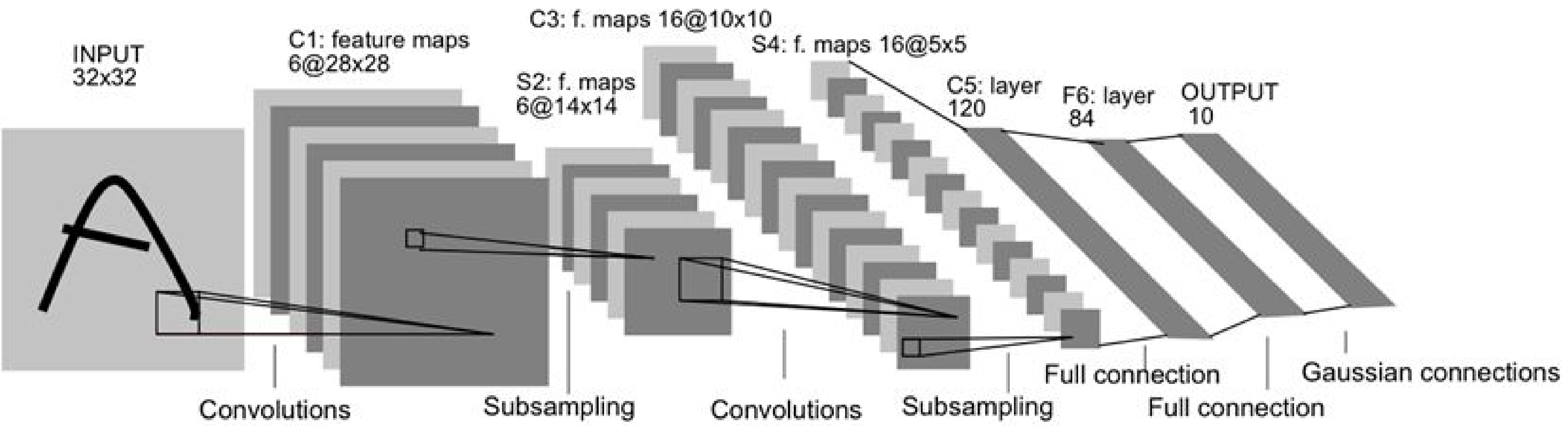


Core algorithm: CNN



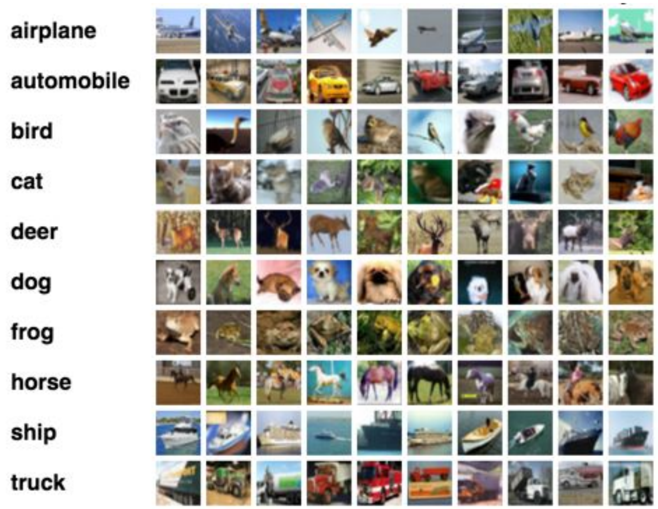
The full connection algorithm of ordinary Neural Network would lead to tremendous computation.

Input image 200*200*3



Implementation

Input:



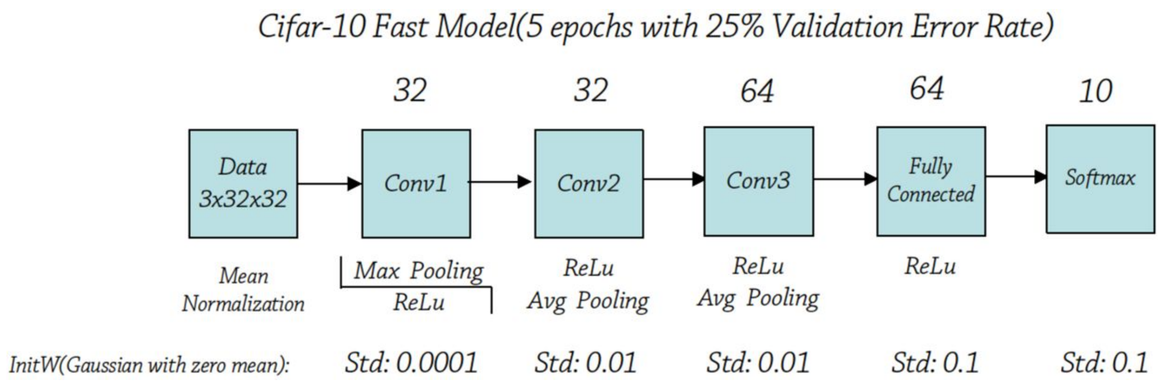
Training images: 50000
(10000 for validation)
Test images: 10000
Class: 10
batch size: 128

Code:

```
# Global constants describing the CIFAR-10 data set.
NUM_CLASSES = 10
NUM_EXAMPLES_PER_EPOCH_FOR_TRAIN = 50000
NUM_EXAMPLES_PER_EPOCH_FOR_EVAL = 10000
# Basic model parameters.
tf.app.flags.DEFINE_integer('batch_size', 128,
                            """Number of images to process in a batch.""")
```

Implementation

Training:



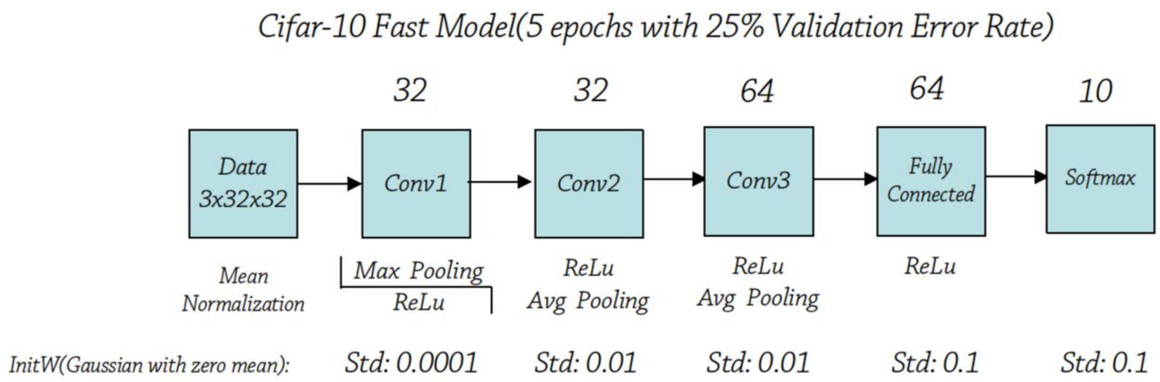
Code: Generate several Convolutional layers

```
# conv1
with tf.variable_scope('conv1') as scope:
  kernel = _variable_with_weight_decay('weights',
                                       shape=[5, 5, 3, 64],
                                       stddev=5e-2,
                                       wd=0.0)
  conv = tf.nn.conv2d(images, kernel, [1, 1, 1, 1], padding='SAME')
  biases = _variable_on_cpu('biases', [64], tf.constant_initializer(0.0))
  bias = tf.nn.bias_add(conv, biases)
  conv1 = tf.nn.relu(bias, name=scope.name)
  _activation_summary(conv1)

# pool1
pool1 = tf.nn.max_pool(conv1, ksize=[1, 3, 3, 1], strides=[1, 2, 2, 1],
                       padding='SAME', name='pool1')
# norm1
norm1 = tf.nn.lrn(pool1, 4, bias=1.0, alpha=0.001 / 9.0, beta=0.75,
                  name='norm1')
```

Implementation

Training:



Code:

The convolution result go through SoftMax first, and then go through fully connected neuron network

```
softmax_linear = tf.add(tf.matmul(local4, weights), biases, name=scope.name)
_activation_summary(softmax_linear)
```

Calculate the loss and gradient and modify the weight and bias.

```
# Compute the moving average of all individual losses and the total loss.
loss_averages = tf.train.ExponentialMovingAverage(0.9, name='avg')
# Compute gradients.
with tf.control_dependencies([loss_averages_op]):
  opt = tf.train.GradientDescentOptimizer(lr)
  grads = opt.compute_gradients(total_loss)
# Apply gradients.
apply_gradient_op = opt.apply_gradients(grads, global_step=global_step)
```

Implementation

Evaluation:

The evaluation runs after evey max_step's steps.

```
tf.app.flags.DEFINE_integer('max_steps', 1000000,
                            """Number of batches to run.""")
```

Track the neuron network information from the check point.

```
saver.restore(sess, ckpt.model_checkpoint_path)
# Assuming model_checkpoint_path looks something like:
#   /my-favorite-path/cifar10_train/model.ckpt-0,
# extract global_step from it.
global_step = ckpt.model_checkpoint_path.split('/')[-1].split('-')[-1]
```

Run the evaluation

```
while True:
  eval_once(saver, summary_writer, top_k_op, summary_op)
  if FLAGS.run_once:
    break
  time.sleep(FLAGS.eval_interval_secs)
```

Experiment setup

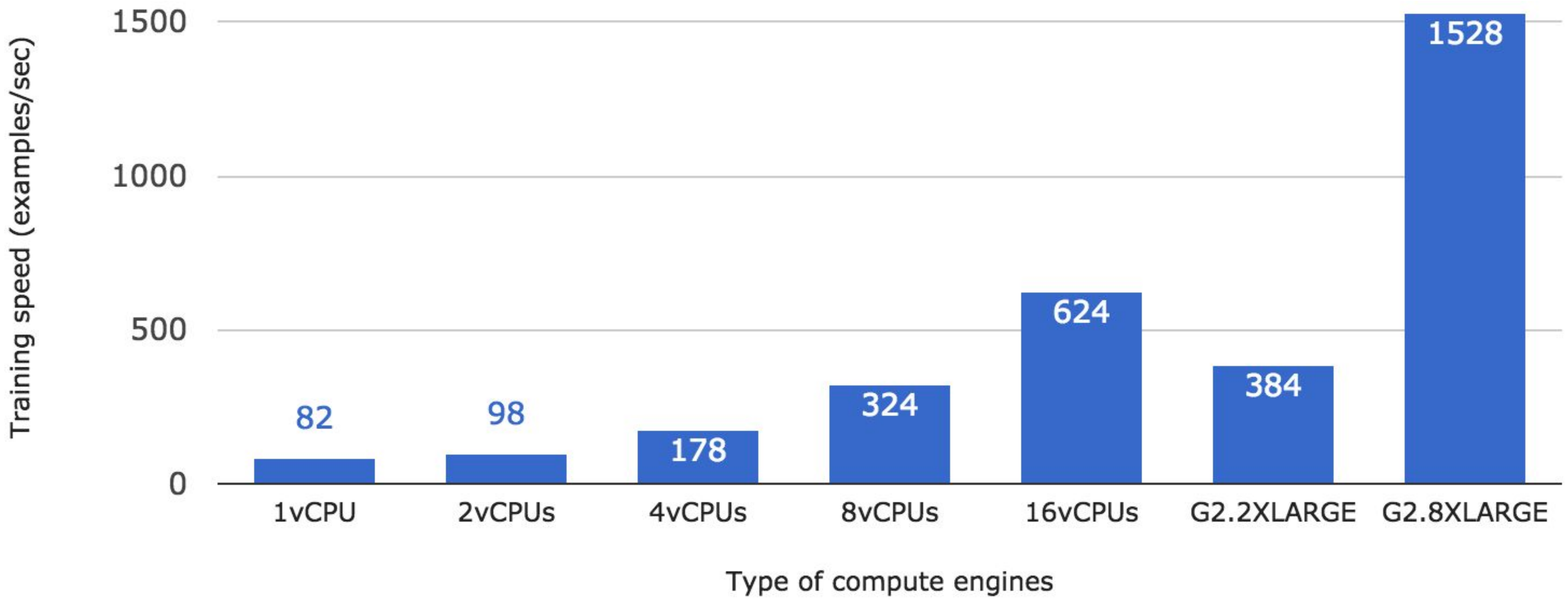
Hardware: AWS GPU instances / gcloud virtual CPUs / Nvidia Tesla K80 GPUs in UF HiperGator 2.0

Software: Ubuntu 14.04 LTS / CUDA 7.5 / cuDNN v5 / TensorFlow 0.11

Metrics: speed / error rate / parameter count / epoch

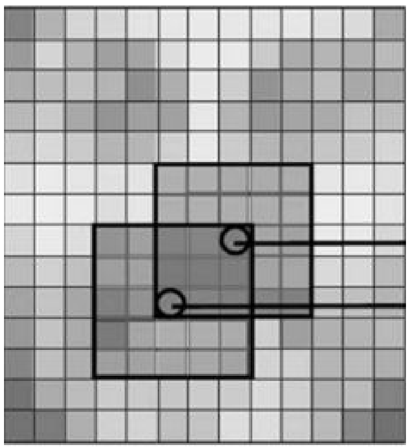
Experiment 1

Speed of different platforms: CPU vs GPU



Experiment 2

Model error rate of overlapping versus nonoverlapping stride of pooling layer scheme.



```
# pool1
pool1 = tf.nn.max_pool(conv1, ksize=[1, 3, 3, 1], strides=[1, 2, 2, 1],
                       padding='SAME', name='pool1')
```

Change the strides of the pooling function and test on both overlapping and nonoverlapping pooling scheme.

Fast 10 epochs Validation Error Rate										
Epoch/Model	1	2	3	4	5	6	7	8	9	10
Overlapping	44%	37%	34%	30%	30%	30%	30%	30%	25%	25%
Not Overlapping	52%	44%	39%	37%	35%	34%	33%	32%	29%	29%

Team Coordination

1. Tianyang the coordinator will continue working on CIFAR-10 with IEEE CNN papers to research on possible ways to increase model performance.
2. Yicheng will work on the ILSVRC2012 dataset and will implement results from Tianyang to train optimized deep CNN models.
3. Su will learn CUDA programming to utilize GPU to train models and also assist Yicheng in model training.
4. All three of us will work on the remaining part like result analyzing and thesis composing.

Future Experiments

1. Repeat experiment results from other papers and rethink advantages of these methods and techniques.
2. Choose then combine stacks of technology into our models through modifying TensorFlow CNN layers.
3. Boost training with CUDA parallelization with reasonable assignment of tasks among kernels and multiple GPUs.
4. Compare overall aspects of the models that we will have trained and optimize one as the final result then compose the final report.

Thank you!

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