训练数据读取

TensorFlow

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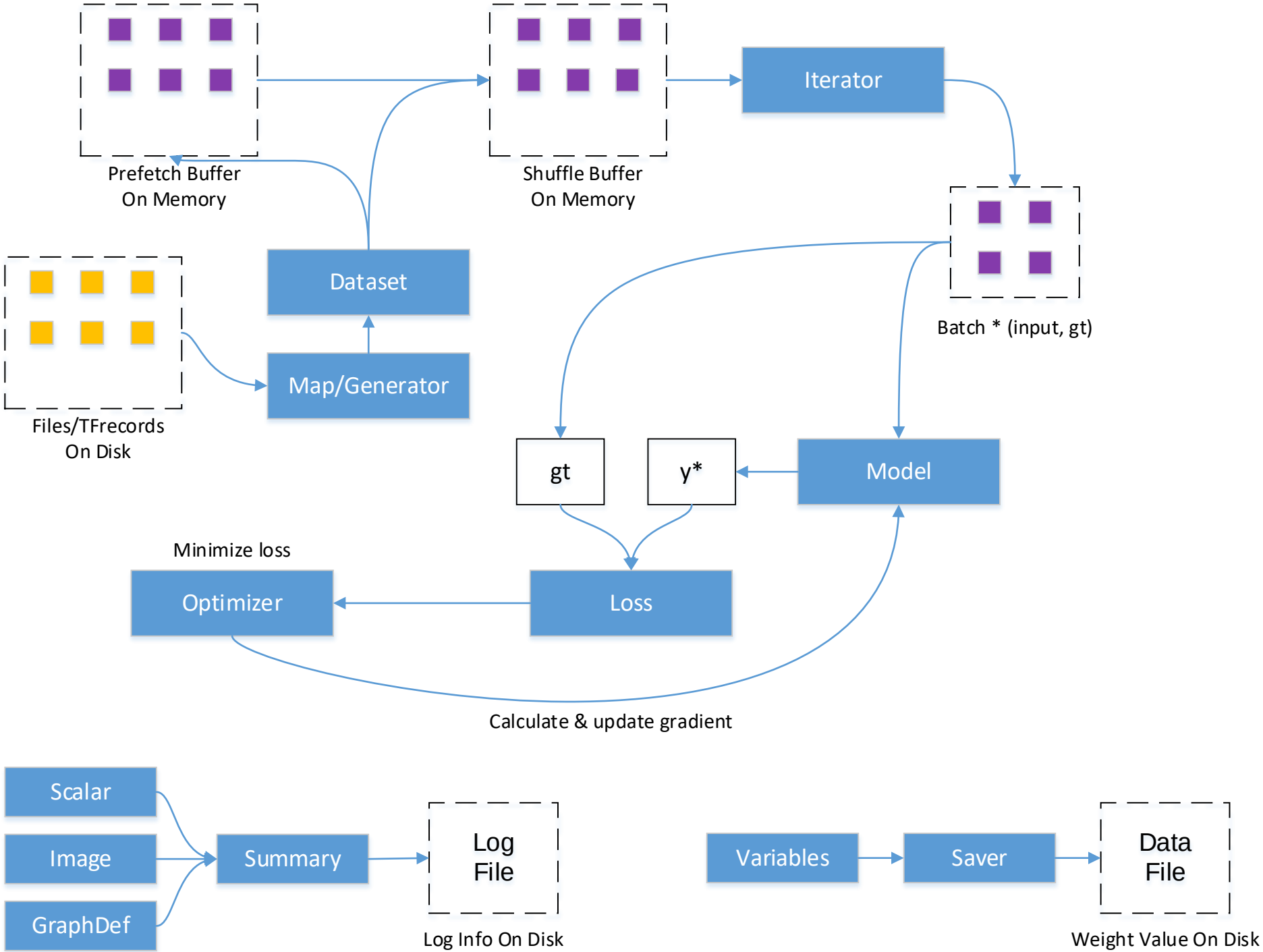
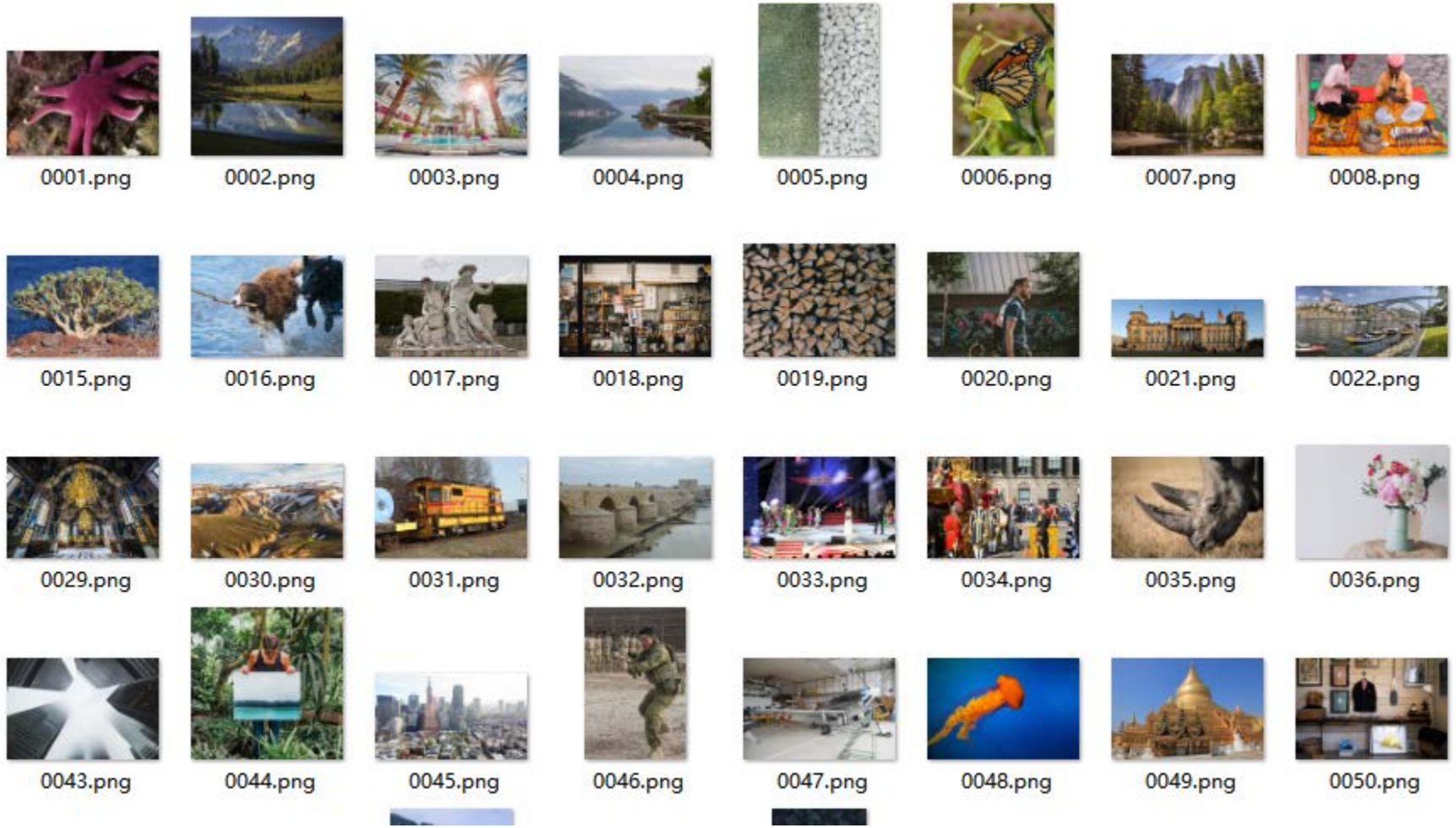

Prefetch Buffer
On Memory
Shuffle Buffer
On Memory
Iterator
Batch * (input, gt)
Dataset
Map/Generator
Files/TFrecords
On Disk
gt
y*
Model
Minimize loss
Optimizer
Loss
Calculate & update gradient
Scalar
Image
GraphDef
Summary
Log
File
Log Info On Disk
Variables
Saver
Data
File
Weight Value On Disk

目的

- 假设4倍超分模型为F
- 监督学习 HR_P = F(LR)
- 需要准备训练数据(LR, HR_GT)

- 训练数据采用DIV2K，一共800张图片
- LR为24x24，HR为96x96
- 生成训练样本：LR [B, 24, 24, 1] 与对应的 HR [B, 96, 96, 1]

DIV2K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0050.png

简介

- 使用tf.data
- 两种读取数据模式：
  - 将原始数据处理成tfrecords数据，再从tfrecords读取
  - 使用生成器generator，直接处理原始数据

定义DataLoader

```python
class DataLoader():
    def __init__(self, data_dir='DIV2K/DIV2K_train_HR',
                 patch_size=96, scale=4, batch_size=64,
                 shuffle_num=2000, prefetch_num=1000,
                 map_parallel_num=8, one_img_patch_num=100):
        self.data_dir = data_dir
        self.patch_size = patch_size
        self.scale = scale
        self.batch_size = batch_size
        self.shuffle_num = shuffle_num
        self.prefetch_num = prefetch_num
        self.map_parallel_num = map_parallel_num
        self.one_img_patch_num = one_img_patch_num
```

生成tfrecords

```python
def gen_tfrecords(self, save_dir='DIV2K/tfrecords', tfrecord_num=10):
    file_num = tfrecord_num
    sample_num = 0
    if not os.path.exists(save_dir):
        os.makedirs(save_dir)
    fs = []
    for i in range(file_num):
        fs.append(tf.python_io.TFRecordWriter(os.path.join(save_dir, 'data%d.tfrecords' % i)))

    img_paths = sorted(glob.glob(os.path.join(self.data_dir, '*.png')))
    for img_path in img_paths:
        print('processing %s' % img_path)
        img = misc.imread(img_path)
        y = utils.img_to_uint8(utils.rgb2ycbcr(img)[:, :, 0])
        height, width = y.shape
        p = self.patch_size
        step = p // 3 * 2
        for h in range(0, height - p + 1, step):
            for w in range(0, width - p + 1, step):
                gt = y[h: h + p, w: w + p]
                assert gt.shape[:] == (p, p)
                assert gt.dtype == np.uint8
                example = tf.train.Example(features=tf.train.Features(feature={
                    'gt': _bytes_feature(gt.tostring())
                }))
                fs[sample_num % file_num].write(example.SerializeToString())
                sample_num += 1
    print('example number: %d' % sample_num)
    np.savetxt(os.path.join(save_dir, 'sample_num.txt'), np.asarray([sample_num]), '%d')
    for f in fs:
        f.close()
```

为什么要生成10个tfrecords?

使用tf.data读取tfrecords

```python
def _parse_one_example(self, example):
    features = tf.parse_single_example(
        example,
        features={
            'gt': tf.FixedLenFeature([], tf.string)
        })
    p = self.patch_size
    gt = features['gt']
    gt = tf.decode_raw(gt, tf.uint8)
    gt = tf.reshape(gt, [p, p])
    gt = tf.cast(gt, tf.float32)

    lr = tf.py_func(lambda x: misc.imresize(x, 1.0 / self.scale, 'bicubic', 'F'), [gt], tf.float32)

    gt = tf.reshape(gt, [p, p, 1]) / 255.0
    lr = tf.reshape(lr, [p // self.scale, p // self.scale, 1]) / 255.0

    c1 = tf.random_uniform([], 0, 1)
    c2 = tf.random_uniform([], 0, 1)
    gt, lr = tf.cond(c1 < 0.5, lambda : (gt[::-1, :], lr[::-1, :]), lambda : (gt, lr))
    gt, lr = tf.cond(c2 < 0.5, lambda: (gt[:, ::-1], lr[:, ::-1]), lambda: (gt, lr))
    return lr, gt

def read_tfrecords(self, save_dir='DIV2K/tfrecords'):
    fs_paths = sorted(glob.glob(os.path.join(save_dir, '*.tfrecords')))
    dataset = tf.data.TFRecordDataset(fs_paths)
    dataset = dataset.map(self._parse_one_example, self.map_parallel_num).shuffle(self.shuffle_num) \
        .prefetch(self.prefetch_num).batch(self.batch_size).repeat()
    lrs, gts = dataset.make_one_shot_iterator().get_next()
    return lrs, gts
```

为什么需要tf.py_func?
优点与缺点？

为什么需要shuffle与prefetch?
Shuffle的大小如何决策？
map/shuffle/batch/repeat调用顺序是否可以交换？

使用tf.data与生成器读取数据

```python
def get_generator(self):
    img_paths = sorted(glob.glob(os.path.join(self.data_dir, '*.png')))
    one_img_patch_num = self.one_img_patch_num
    p = self.patch_size
    scale = self.scale
    for img_path in img_paths:
        img = misc.imread(img_path)
        height, width, _ = img.shape
        for i in range(one_img_patch_num):
            h = np.random.randint(height - p + 1)
            w = np.random.randint(width - p + 1)
            patch = img[h: h + p, w: w + p]
            gt = utils.rgb2ycbcr(patch)[:, :, 0]
            gt = np.float32(gt)
            lr = misc.imresize(gt, 1.0 / scale, 'bicubic', 'F')
            gt = gt / 255.0
            lr = lr / 255.0
            c1 = np.random.rand()
            c2 = np.random.rand()
            if c1 < 0.5:
                gt, lr = gt[::-1, :], lr[::-1, :]
            if c2 < 0.5:
                gt, lr = gt[:, ::-1], lr[:, ::-1]
            yield lr, gt

def read_pngs(self):
    dataset = tf.data.Dataset.from_generator(self.get_generator, (tf.float32, tf.float32))
    dataset = dataset.shuffle(self.shuffle_num).prefetch(self.prefetch_num).batch(self.batch_size).repeat()
    lrs, gts = dataset.make_one_shot_iterator().get_next()
    p = self.patch_size
    lrs = tf.reshape(lrs, [-1, p // self.scale, p // self.scale, 1])
    gts = tf.reshape(gts, [-1, p, p, 1])
    return lrs, gts
```

使用tfrecords读取与generator读取数据各有什么优点？两者分别的应用场景？

测试

```
if __name__ == '__main__':
    os.environ['CUDA_VISIBLE_DEVICES'] = '-1'
    data_loader = DataLoader()
    # data_loader.gen_tfrecords()
    # lrs, gts = data_loader.read_tfrecords()
    lrs, gts = data_loader.read_pngs()
    sess = tf.Session()
    # import matplotlib.pyplot as plt
    # while True:
    #     im1, im2 = sess.run([lrs, gts])
    #     plt.imshow(utils.img_to_uint8(im2[0, :, :, 0]))
    #     plt.show()
    im1, im2 = sess.run([lrs, gts])
    print(im1.shape, im2.shape)

Out: (64, 24, 24, 1) (64, 96, 96, 1)
```

两者性能对比

- 左：TFrecords　右：Generator

```
[0:00:06.458232] Step:360, loss:2.1939547061920166
[0:00:06.360591] Step:380, loss:1.7203850746154785
[0:00:06.497405] Step:400, loss:1.697927474975586
[0:00:06.392951] Step:420, loss:1.917050838470459
[0:00:06.406135] Step:440, loss:1.6480821371078491
[0:00:06.414975] Step:460, loss:2.2578155994415283
[0:00:06.417290] Step:480, loss:2.329984664916992
[0:00:06.418469] Step:500, loss:2.050870895385742
[0:00:06.424043] Step:520, loss:2.2898924350738525
[0:00:06.477182] Step:540, loss:1.6806976795196533
[0:00:06.477095] Step:560, loss:2.147488594055176
[0:00:06.354545] Step:580, loss:2.4012746810913086
[0:00:06.344338] Step:600, loss:1.7057498693466187
[0:00:06.330753] Step:620, loss:2.389599323272705
```

```
[0:00:06.470682] Step:40, loss:2.406553268432617
[0:00:06.368222] Step:60, loss:1.9597632884979248
[0:00:06.360373] Step:80, loss:2.01263165473938
[0:00:06.367866] Step:100, loss:2.0152368545532227
[0:00:06.433587] Step:120, loss:1.6612085103988647
[0:00:06.547826] Step:140, loss:2.1646509170532227
[0:00:06.403579] Step:160, loss:1.538785696029663
[0:00:06.533406] Step:180, loss:2.132829427719116
[0:00:06.523904] Step:200, loss:2.5021376609802246
[0:00:06.421889] Step:220, loss:3.3712172508239746
[0:00:06.413011] Step:240, loss:2.381728410720825
```