Data Science Lab Tooth Detection Project 2조 최종보고



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1. 학습 내용

<Object Detection 개념 학습 및 프로젝트>

- 1. Object Detection 이해
 - Object Detection 문제영역 이해
 - Object Detection Metric: IoU, mAP
 - Pascal VOC, MS COCO, KITTI, Open Images
- 2. Google Colab, Tensorflow Object Detection API 학습
- 3. 대표적 Object Detection 모델 학습
 - R-CNN
 - Fast R-CNN
 - Faster R-CNN
 - Non-Maximum Suppression (NMS)
 - SSD (Single Shot Multibox Detector)
 - RetinaNet
 - CenterNet
- 4. Pre-Trained Object Detection Model 적용 프로젝트
 - Faster R-CNN을 이용한 Person Detection, Autopilot Detection, License Plate Detection Project
 - CenterNet을 이용한 Car Detection, Human Pose Estimation Project
 - SSD를 이용한 Face Detection Project

<Object Detection 논문 리뷰 스터디>

- 1. R-CNN 논문 리뷰
- 2. Fast R-CNN 논문 리뷰
- 3. Faster R-CNN 논문 리뷰
- 4. YOLO 논문 리뷰
- 5. SSD 논문 리뷰
- 6. VGGNet 논문 리뷰

2. 사용한 코드 설명

<[DSL]Tooth_Detection_Model.ipynb 파일 구성>

- 0. Default Setting
- 1. Install Tensorflow object detection API
- 2. Prepare Train data and EDA
- 3. Download TF Pretrained Models
- 4. Copy Model Config to Training Folder
- 5. Update Config for Transfer Learning
- 6. Train the model
- 7. Evaluate the Model
- 8. Detect from an Image
- 9. Model check with Tensorboard and checkpoint
- 10. Freezing the Graph
- 11. Conversion to TFLite
- 12. Zip and Export Models

0. Default Setting

0. Default Setting

```
Executed in Colab pro environment.

    ML Framework

    Python 3.7.11

    Tensorflow 2.5.0

                 o RAM: 12.7G
                 o CPU: Intel(R) Xeon(R) CPU @ 2.30GHz (1core)
[] # Check GPU Availability
spu_info = !nvidia-smi
spu_info = !mvioin(spu_info)
if spu_info.find('failed') >= 0:
print('Select the Runtime > "Change runtime type" menu to enable a GPU accelerator, ')
print('and then re-execute this cell.')
              print(gpu_info)
           Select the Runtime > "Change runtime type" menu to enable a GPU accelerator, and then re-execute this cell.
[ ] # Library import
           # Library import import of import os import jeon import os import so import experimental import material import material import material import material import material import material import configurial from object_detection.purtos import pipeline_pb2 from google.protobul import text_format import text_format import manuely as np
[] # Google Drive mount
from google.colab import drive
drive.mount('<u>/content/drive</u>')
```

딥러닝 모델을 다루기 이전에 모델, 데이터를 가져오는 과정으로 기본 환경을 설정하는 준비 단계이다. 딥러닝 모델을 빠르게 돌리기 위한 Colab pro의 RAM, GPU환경 설정에 대해 확인 하고 모델, config파일, Data set(충치이미지 데이터)를 불러오기 위한 코드이다.

1. Install Tensorflow object detection API

1. Install Tensorflow object detection API

```
| Time |
```

Object detection을 하기 위해 Tensorflow기반으로 만들어진 Tensorflow object detection API를 설치하는 코드이다.

2. Prepare Train data and EDA

2. Prepare Train data and EDA

```
[ ] %%capture
    %%bash
    # Prepare train data
    # Copy and unzip dataset in wd
    # Modify below directory properly based on your environment
    cp '/content/drive/MyDrive/Corporation_Project/tooth-sample-dsl(original).zip' '/content/tooth-sample-dsl.zip'
    unzip -q '/content/tooth-sample-dsl.zip' -d '/content/TensorFlow
[ ] # Creating definition file(.pbtxt)
    labels = [{'name':'normal', 'id':1}, {'name':'caries', 'id':2}, ]
    !mkdir '/content/TensorFlow/tooth-sample-dsl/annotations'
    for label in labels:
           f.write('item { \m')
           f.write('\tmame:\tmame:\tmame'\}\tmame'\tmame'))
           f.write('\tid:{}\tin'.format(label['id']))
           f.write('}\m')
```

mkdir: cannot create directory '/content/TensorFlow/tooth-sample-dsl/annotations' : File exists

```
def get_num_classes(pbtxt_fname):
    from object_detection.utils import label_map_util
    label_map = label_map_util.load_labelmap(pbtxt_fname)
    categories = label_map_util.convert_label_map_to_categories(
        label_map, max_num_classes=90, use_display_name=True)
    category_index = label_map_util.create_category_index(categories)
    return len(category_index.keys())
```

모델을 훈련시키기 위한 준비를 하는 코드로, 데이터와, 데이터에 대한 간단한 EDA를 하는 과정이다. train data(압축파일)를 불러와, 압축을 풀고, 데이터에 대한 정의서가 들어있는 pbtxt를 만들고 pbtxt 파일안에 데이터가 잘 정의되어 있는지 확인하기 위한 함수를 짠 코드이다.

```
[ ] # Get num_classes of pbtxt file (1: normal, 2: caries)

wd = '/content/TensorFlow/tooth-sample-dsl'
pbtxt_fname = os.path.join(wd, 'annotations', 'caries_map.pbtxt')
get_num_classes(pbtxt_fname)
2
```

pbtxt파일의 class의 수를 출력한 결과, 2로 1: normal(정상), 2: caries(충치)로 잘 정의되어 있는 것을 확인할 수 있다.

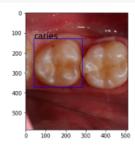
```
[] # Check data
dir_path = '/content/TensorFlow/tooth-sample-dsl'
imgs = natsorted([i for i in os.listdir(dir_path + '/img_train') if i.startswith('Folder')])
jsons = natsorted([i for i in os.listdir(dir_path + '/json_train') if i.startswith('Folder')])
print(len(imgs))
print(len(jsons))

1734
```

1734개의 데이터도 모두 잘 불러와졌는지 개수를 통해 확인하였다.

```
[] # Check sample
       def show sample tooth(img index):
            with open(os.path.join(dir_path, 'json_train', jsons[img_index]), 'r') as f:
            sample_img = cv2.imread(os.path.join(dir_path, 'img_train', imgs[img_index]))
sample_img = cv2.cvtColor(sample_img, cv2.COLOR_BGR2RGB)
            plt.imshow(sample_img)
            fig = plt.gca()
for i,a in enumerate(data['annotation']['regions']):
    attr = a['shape_attributes']
                 label = a['region_attributes']['label']
if label == 'normal':
                 fig.add_patch(mpl.patches.Rectangle(xy = (attr['x'], attr['y']),
                                                width = attr['width'],
height = attr['height'],
                                                 alpha=1.
                                                color='blue',
                                                fill=None))
                 fig.text(attr['x'], attr['y'],
                            Tabel.
                           size=15)
            plt.show()
```

[] show_sample_tooth(777)



이미지 데이터가 잘 불러져 왔는지 실질적으로 확인하기 위한 코드로, 데이터가 잘 불러와졌고, patch를 통해 충치만을 체크하도록 표시함으로써, labeling이 충치에만 되고 있는 것인지 확인했다.

3. Download TF Pretrained Models

3.Download TF Pretrained Models

```
[] # Setting pre-traind-models folder & variables
Imkdir /content/TensorFlow/tooth-sample-dsi/pre-trained-models'
CUSTOM_MODEL_NAME = 'my_ssd_mobnet'
PRETRAINED_MODEL_NAME = 'ssd_mobilenet_v2_fpnlite_320x320_cocol?_tpu-8'
PRETRAINED_MODEL_NAME = 'ssd_mobilenet_v2_fpnlite_320x320_cocol?_tpu-8'
PRETRAINED_MODEL_NAME = 'generate_tfrecord.py'
LABEL_MAP_NAME = 'generate_tfrecord.py'
LABEL_MAP_NAME = 'generate_tfrecord.py'
LABEL_MAP_NAME = 'caries_map_pbtxt'

[] # Setting paths of pre-trained model

paths = {
    "UURKSPACE_PATH': os.path.join(os.getcwd(), 'TensorFlow', 'tooth-sample-dsl', 'nanotations'),
    "ANOMATION_PATH': os.path.join(os.getcwd(), 'TensorFlow', 'tooth-sample-dsl', 'inages_train'),
    "NAMOTATION_PATH': os.path.join(os.getcwd(), 'TensorFlow', 'tooth-sample-dsl', 'inages_train'),
    "IMAGE_TRAIN_PATH': os.path.join(os.getcwd(), 'TensorFlow', 'tooth-sample-dsl', 'inages_train'),
    "MODEL_PATH': os.path.join(os.getcwd(), 'TensorFlow', 'tooth-sample-dsl', 'inages_train'),
    "MODEL_PATH': os.path.join(os.getcwd(), 'TensorFlow', 'tooth-sample-dsl', 'inages_train'),
    "CHECKPOINT_PATH': os.path.join(os.getcwd(), 'TensorFlow', 'tooth-sample-dsl', 'models', CUSTOM_MODEL_NAME, 'tensort'),
    "TENS_PATH': os.path.join(os.getcwd(), 'TensorFlow', 'tooth-sample-dsl', 'models', CUSTOM_MODEL_NAME, 'tflitexport'),
    "TENS_PATH': os.path.join(os.getcwd(), 'TensorFlow', 'tooth-sample-dsl', 'models', C
```

이미 훈련되어있는 ssd_mobilenet _v2_fpnlite_32 0_x320_coco17_tpu-8를 기반으로 충치구별모델을 만들기 위해 모델을 다운로드하고 'tooth-sample-dsl'이라는 경로를 설정함으로써 모델을 복사하기 위한 준비를 했다.

4. Copy Model Config to Training Folder

4. Copy Model Config to Training Folder

모델을 훈련시키기 위해 우리의 training 폴더에 모델 config를 복사했다. (ssd_mobilenet _v2_fpnlite_32 0_x320_coco17_tpu-8에서 hyperparameter를 직접 수정하기 위해 우리파일에 복사해온 것이다.)

5. Update Config for Transfer Learning

우리 training 폴더에 복사되어 있는 conifg파일에서 모델의 hyperparameter를 직접 수정하는 코드이다. 이를 훈련 모델의 config로 사용하기 위해 수정이 끝난 config파일인 pipeline_config를 PIPELINE_CONFG 파일로 보냄으로써 수정을 반영한다.

6. Train the model



위에서 ssd_mobilenet _v2_fpnlite_32 0_x320_coco17_tpu-8 모델의 config를 수정하여 만든 모델을 Train 시키기 위한 코드이다. num_train_steps로 train step수를 조절하고, 우리가 수정한 config를 가져오기 위해 경로(checkpoint_path)와 config파일(PIPELINE_CONFIG)를 train command에 넣은 것이다.

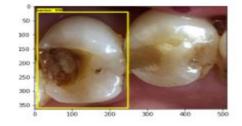
7. Evaluate the Model

7. Evaluate the Model

Train된 모델의 성능을 확인할 수 있는 evaluation 코드이다. !{command}하단의 코드 결과 중, Average Precision (AP)중 IoU=0.5:0.95, IoU=0.5의 mAP값을 기준으로 모델의 성능을 평가했다.

8. Detect from an Image

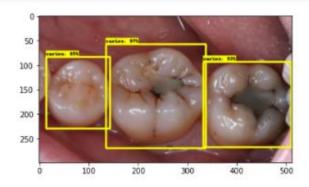
```
[ ] # Executing inference using trained detection_model
           # Loading image
img = cv2.imread(image_src)
           Image_np - np.array(Img)
           Input_tensor = tf.convert_to_tensor(np.expand_dims(image_np, 0), dtype=tf.float82)
detections = detect_fn(input_tensor)
           num_detections = int(detections.pop('num_detections'))
          detections = {key: value[0, :num_detections].numpy() for key, value in detections.items()} detections['num_detections'] = num_detections
          # Detection_classes should be inta
detections['detection_classes'] = detections['detection_classes'].sstype(np.int84)
           label_id_offset - 1
            Image_np_with_detections = image_np.copy()
          # Screening only cavity(label2 in potxt file)
screening = np.where(detections['detection_classes'] < 1)
detections['detection_boxes'] = np.delete(detections['detection_boxes'].screening[0], axis = 0)
detections['detection_classes'] = np.delete(detections['detection_classes'].screening[0])
detections['detection_scores'] = np.delete(detections['detection_scores'].screening[0])
detections['raw_detection_boxes'] = np.delete(detections['raw_detection_boxes'].screening[0])
detections['detection_multiclass_scores'] = np.delete(detections['detection_scores'].screening[0])
detections['detection_multiclass_scores'] = np.delete(detections['detection_anchor_indices'].screening[0])
           # Visualizing Inference
           viz_utils.visualize_boxes_and_labels_on_image_array(
                                    Image_np_with_detections,
                                  detections['detection_boxes'],
detections['detection_classes']+label_id_offset,
detections['detection_scores'],
                                  category_index,
use_normalized_coordinates=True,
                                   max_boxes_to_draw=5.
                                  min_score_thresh=.6,
agnostic_mode=False)
           pit.imshow(cv2.cvtColor(image_np_with_detections, cv2.COLOR_BGR2RGB))
```



새로운 충치 이미지 데이터를 불러와 훈련시킨 모델이 새로운 충치 이미지에서도 carries(충치)를 잘 구분해내는지 확인하는 코드로, 결과값으로 나온 이미지를 통해 labeling이 잘 되어있는 것을 통해 모델이 carries(충치)를 잘 구분해내고 있음을 확인할 수 있다.

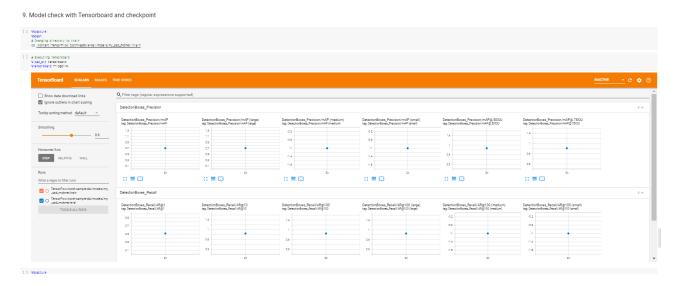
```
[] # Function for executing inference and saving into image file
     import imageio
     # Setting folder path
     output_folder = '/content/TensorFlow/tooth-sample-dsl/test_image_predict_result'
     def predict_and_save_result(IMAGE_PATH, min_score_thresh = 0.5):
       img = cv2.imread(IMAGE_PATH)
       image_np = np.array(img)
       input_tensor = tf.convert_to_tensor(np.expand_dims(image_np, 0), dtype=tf.float32)
       detections = detect_fn(input_tensor)
       num_detections = int(detections.pop('num_detections'))
       detections = {key: value[0, :num_detections].numpy() for key, value in detections.items()}
       detections['num_detections'] = num_detections
       # detection_classes should be ints.
       detections['detection_classes'] = detections['detection_classes'].astype(np.int64)
       label_id_offset = 1
       image_np_with_detections = image_np.copy()
       # Screening only cavity(label2 in pbtxt file)
       screening = np.where(detections['detection_classes'] < 1)</pre>
       detections['detection_boxes'] = np.delete(detections['detection_boxes'], screening[0], axis = 0)
       detections['detection_classes'] = np.delete(detections['detection_classes'], screening[0])
       detections['detection_scores'] = np.delete(detections['detection_scores'], screening[0])
       detections['raw_detection_boxes'] = np.delete(detections['raw_detection_boxes'], screening[0], axis = 0)
       detections['detection_multiclass_scores'] = np.delete(detections['detection_multiclass_scores'], screening[0], axis = 0)
       detections['detection_anchor_indices'] = np.delete(detections['detection_anchor_indices'], screening[0])
       # Visualizing inference
       viz_utils.visualize_boxes_and_labels_on_image_array(
                 image_np_with_detections,
                 detections['detection_boxes'],
                 detections['detection_classes']+label_id_offset,
                 detections['detection_scores'],
                 category_index,
                 use_normalized_coordinates=True,
                 max_boxes_to_draw=5,
                 min_score_thresh=.8,
                 agnostic_mode=False)
       plt.imshow(cv2.cvtColor(image_np_with_detections, cv2.COLOR_BGR2RGB))
       plt.savefig(os.path.join(output_folder,'[Result]' + IMAGE_PATH.split('/')[-1]))
```

[] # Sample image inference testing predict_and_save_result(IMAGE_PATH = image_src)



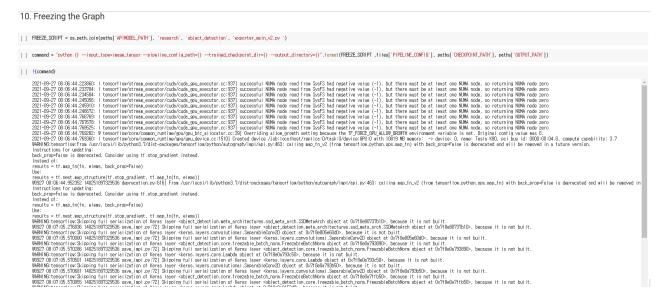
훈련시킨 모델로 충치 데이터에서 충치를 구별해낸 결과인 labeling된 이미지를 이미지 파일로 저장하기 위한 함수를 정의하는 코드이다. 우측의 sample그림을 보면 세개의 충치도 잘 구별해내는 것을 labeling과, 그림에 표시된 accuracy를 통해 확인할 수 있다.

9. Model check with Tensorboard and checkpoint



Tensorboard의 Checkpoint를 통해 모델을 확인하였다.

10. Freezing the Graph



Freezing the graph를 통해 그래프와 체크포인트 변수에 대한 정보를 포함하는 단일 파일을 생성한다. 우리가 수정한 hyperparmeter를 그래프 구조 내의 상수로 저장함으로써, 반복해서 똑같은 모델의 정확도로 충치를 구분하도록 하기 위한 과정이다.

11. Conversion to TFLite

11. Conversion to TFLite

```
| Full Country | Country |
```

TFLite로 변환함으로써 mobile, embedded machine에서의 모델을 사용할 수 있도록 했다.

12. Zip and Export Models

12. Zip and Export Models

```
[] # Export Models as tar.gz file
!tar -czf models.tar.gz {paths['CHECKPOINT_PATH']}
tar: Removing leading '/' from member names
```

이 모델을 압축하여 밖으로 추출하는 과정이다.

3. 모델 학습 결과 및 인사이트

Train Step 과 Batch Size 조정					
Pretrained Model	Train Steps	mAP (IOU 0.5)	mAP (IOU 0.5:0.95)	수정한 parameter	
ssd_mobilenet _v2_fpnlite_32 0_x320_coco17_tpu-8	4000	0.765	0.632	Batch_size=70 Iou_threshold=0.58 Batch_norm.decay=0.998 classification_weight=1.25 localization_weight=1.25	
ssd_mobilenet _v2_fpnlite_32 0_x320_coco17_tpu-8	4000	0.779	0.779	Batch_size=55 Iou_threshold=0.58 Batch_norm.decay=0.998 classification_weight=1.25 localization_weight=1.25	
ssd_mobilenet _v2_fpnlite_32 0_x320_coco17_tpu-8	2500	0.777	0.625	Batch_size=40 Iou_threshold=0.58 Batch_norm.decay=0.998 classification_weight=1.25 localization_weight=1.25	
ssd_mobilenet _v2_fpnlite_32 0_x320_coco17_tpu-8	2500	0.728	0.556	Batch_size=20 Iou_threshold=0.58 Batch_norm.decay=0.998 classification_weight=1.25 localization_weight=1.25	

Train step 과 batch size 를 변화시켜본 결과, batch size 가 40, 55 일 때 가장 높은 결과값을 보여주었다. 또한, train step 을 무조건 늘린다고 성능이 좋아지는 것이 아니라는 것을 확인할 수 있었다.

Aspect	Ratio	조정

Pretrained Model	Train	mAP	mAP	수정한 parameter
	Steps	(IOU 0.5)	(IOU 0.5:0.95)	, 5 = 1
ssd_mobilenet	2000	0.819893	0.651016	Batch_size=20
_v2_fpnlite_32				Classification_weight=1.1
0_x320_coco17_tpu-8				Localization_weight=1.0
				Aspect_ratio=3.0 / 0.3
ssd_mobilenet	2000	0.823996	0.675252	Batch_size=50
_v2_fpnlite_32				Classification_weight=1.1
0_x320_coco17_tpu-8				Localization_weight=1.25
				Aspect_ratio=3.0 / 0.3
ssd_mobilenet	2000	0.834240	0.667254	Batch_size=75
_v2_fpnlite_32				Classification_weight=1.25
0_x320_coco17_tpu-8				Localization_weight=1.25
ssd_mobilenet	2000	0.824226	0.628054	Batch_size=20
_v2_fpnlite_32				Classification_weight=1.1
0_x320_coco17_tpu-8				Localization_weight=1.0
				Aspect_ratio=2.85 / 0.35
ssd_mobilenet	2000	0.803816	0.656874	Batch_size=50
_v2_fpnlite_32				Classification_weight=1.1
0_x320_coco17_tpu-8				Localization_weight=1.25
				Aspect_ratio=2.85 / 0.35

ssd_mobilenet	2000	0.881516	0.718	Batch_size=50
_v2_fpnlite_32				Classification_weight=1.25
0_x320_coco17_tpu-8				Localization_weight=1.25
				Aspect_ratio=2.85 / 0.35
I al Al	7 7 1 6	-0 -0 A) -1	10 11-11-11-1-1) 0.05 / 0.05 7

최적의 aspect ratio 를 찾기 위해 다양한 조합을 실행해본 결과, aspect ratio 가 2.85 / 0.35 로 설정되었을 때 가장 좋은 결과값을 도출한다는 것을 알 수 있었다.

Classification_weight 조정					
Pretrained Model	Train	mAP	mAP	수정한 parameter	
	Steps	(IOU 0.5)	(IOU 0.5:0.95)		
ssd_mobilenet	2000	0.862439	0.676	Batch_size=20	
_v2_fpnlite_32				Classification_weight=1.2	
0_x320_coco17_tpu-8				Learning_rate_base=0.02	
				Warmup_learning_rate=0.01	
ssd_mobilenet	3000	0.882	0.701	Batch_size=20	
_v2_fpnlite_32				Classification_weight=1.1	
0_x320_coco17_tpu-8				Learning_rate_base=0.02	
				Warmup_learning_rate=0.01	
ssd_mobilenet	3000	0.836158	0.673	Batch_size=20	
_v2_fpnlite_32				Classification_weight=1.0	
0_x320_coco17_tpu-8				Learning_rate_base=0.02	
				Warmup_learning_rate=0.01	

Classification weight 변수는 1.0일 때보다 1.1 혹은 1.2로 올렸을 때 더 좋은 결과값을 배출한다는 것을 알 수 있었다.

Batch_size, classification_weight, localization_weight 조정					
Pretrained Model	Train	mAP	mAP	수정한 parameter	
	Steps	(IOU 0.5)	(IOU 0.5:0.95)		
ssd_mobilenet	2000	0.864	0.726	Batch_size=32	
_v2_fpnlite_32				Classification_weight=1.25	
0_x320_coco17_tpu-8				Learning_rate_base=0.03	
				Localization_weight=1.25	
ssd_mobilenet	2000	0.861	0.709	Batch_size=50	
_v2_fpnlite_32				Classification_weight=1.25	
0_x320_coco17_tpu-8				Learning_rate_base=0.03	
				Localization_weight=1.25	
ssd_mobilenet	2000	0.864	0.726	Batch_size=50	
_v2_fpnlite_32				Classification_weight=1.15	
0_x320_coco17_tpu-8				Learning_rate_base=0.03	
				Localization_weight=1.15	
ssd_mobilenet	2000	0.892	0.748	Batch_size=50	
_v2_fpnlite_32				Classification_weight=1.2	
0_x320_coco17_tpu-8				Learning_rate_base=0.03	
ssd_mobilenet	2000	0.851	0.701	Batch_size=50	
_v2_fpnlite_32				Classification_weight=1.25	
0_x320_coco17_tpu-8				Learning_rate_base=0.03	
ssd_mobilenet	2000	0.883	0.722	Batch_size=50	
_v2_fpnlite_32				Classification_weight=1.3	
0_x320_coco17_tpu-8	ما ا			Learning_rate_base=0.03	

Classification weight 와 localization weight는 1.0~1.25 사이로 동시에 변경해보았을 때에는 별다른 차이가 없었지만 Classification_weight만 1.2로 높였을 때 결과값이 크게 향상했으며 1.2이상으로 높이자 다시 하락하는 경향을 보였다.

Batch size 의 32 와 50 사이에는 큰 결과값 차이가 있지 않았다.

Iou_threshold 조정						
Pretrained Model	Train Steps	mAP (IOU 0.5)	mAP (IOU 0.5:0.95)	수정한 parameter		
ssd_mobilenet _v2_fpnlite_32 0_x320_coco17_tpu-8	3000	0.776	0.624	Batch_size=100 Iou_threshold=0.57 Batch_norm.decay=0.998		
ssd mobilenet	2500	0.788	0.619	classification_weight=1.25 localization_weight=1.25 Batch_size=100		
_v2_fpnlite_32 0_x320_coco17_tpu-8	2000	0.766	0.019	Iou_threshold=0.58 Batch_norm.decay=0.998 classification_weight=1.25 localization_weight=1.25		
Train step 을 500 중	였음에도 별	<u> </u> 불구하고 기존 (│ Ი 6N ㅇㄹ 석젓되어	있던 Non-max suppression 의		
_		MAP 값이 약		ı_throshold 를 낮추는 방향으로		
	Iou_	threshold, Ba	tch_norm.decay 조	<u>-</u> 정		
Pretrained Model	Train Steps	mAP (IOU 0.5)	mAP (IOU 0.5:0.95)	수정한 parameter		
ssd_mobilenet _v2_fpnlite_32 0_x320_coco17_tpu-8	4000	0.793	0.648	Batch_size=20 Iou_threshold=0.58 Batch_norm.decay=0.998 classification_weight=1.25 localization_weight=1.25		
ssd_mobilenet _v2_fpnlite_32 0_x320_coco17_tpu-8	4000	0.778	0.633	Batch_size=20 Batch_norm.decay=0.998 classification_weight=1.25 localization_weight=1.25		
ssd_mobilenet _v2_fpnlite_32 0_x320_coco17_tpu-8	4000	0.776	0.625	Batch_size=20 Iou_threshold=0.58 classification_weight=1.25 localization_weight=1.25		
			ou_threshold 조정	3 -1 -1		
Pretrained Model	Train Steps	mAP (IOU 0.5)	mAP (IOU 0.5:0.95)	수정한 parameter		
ssd_mobilenet _v2_fpnlite_32 0_x320_coco17_tpu-8	2000	0.892	0.748	Batch_size=50 Learning_rate_base=0.03 Classification_weight=1.2 Iou_threshold=0.6		
ssd_mobilenet _v2_fpnlite_32 0_x320_coco17_tpu-8	3000	0.884	0.707	Batch_size=50 Learning_rate_base=0.03 Classification_weight=1.2 Iou_threshold=0.6		
ssd_mobilenet _v2_fpnlite_32 0_x320_coco17_tpu-8	2000	0.879	0.732	Batch_size=50 Learning_rate_base=0.03 Classification_weight=1.2 Iou_threshold=0.5		
ssd_mobilenet _v2_fpnlite_32 0_x320_coco17_tpu-8	2500	0.862	0.702	Batch_size=50 Learning_rate_base=0.03 Classification_weight=1.2 Iou_threshold=0.5		

Non_max_suppresion의 iou_threshold를 0.5로 낮춰본 결과, 결과값이 떨어졌다. 또한, Train_step을 2000에서 2500과 3000으로 늘려본 결과, 미세하게 결과값이 떨어지는 것을 확인할 수 있었다.

따라서, train_step 은 2000, iou_threshold 는 처음 주어진 0.6 으로 설정해두기로 하였다.

Batch_norm.decay 조정					
Pretrained Model	Train	mAP	mAP	수정한 parameter	
	Steps	(IOU 0.5)	(IOU 0.5:0.95)		
ssd_mobilenet	3000	0.787	0.663	Batch_size=50	
_v2_fpnlite_32				Iou_threshold=0.58	
0_x320_coco17_tpu-8				Batch_norm.decay=0.004	
				classification_weight=1.2	
				localization_weight=1.2	
				learning_rate_base=0.08	
ssd_mobilenet	3000	0.726	0.584	Batch_size=50	
_v2_fpnlite_32				Iou_threshold=0.58	
0_x320_coco17_tpu-8				Batch_norm.decay=0.004	
				classification_weight=1.2	
				localization_weight=1.2	

Batch_norm.decay 를 0.998 에서부터 0.004 까지 변화시켜본 결과, 결과값에 큰 차이를 불러일으키지 않는 것으로 보아 batch_norm.decay 는 모델 성능에 큰 영향을 끼치지 않는 것으로 판단하여 수정하지 않기로 하였다.

Learning_rate 조정					
Pretrained Model	Train	mAP	mAP	수정한 parameter	
	Steps	(IOU 0.5)	(IOU 0.5:0.95)		
ssd_mobilenet	2000	0.892	0.748	Batch_size=50	
_v2_fpnlite_32				Learning_rate_base=0.03	
0_x320_coco17_tpu-8				Classification_weight=1.2	
ssd_mobilenet	2500	0.826	0.63	Batch_size=50	
_v2_fpnlite_32				Learning_rate_base=0.01	
0_x320_coco17_tpu-8				Warmup_learning_rate=0.005	
				Classification_weight=1.25	

최상값을 기준으로 learning rate 를 0.03에서 0.01로 바꿔본 결과, 결과값이 떨어진 것으로 보아, learning rate 는 0.03으로 두는 것이 최선의 선택일 것이라고 판단했다.

	그 외 시도해본 parameter 조합과 성능					
Pretrained Model	Train	mAP	mAP	수정한 parameter		
	Steps	(IOU 0.5)	(IOU 0.5:0.95)			
ssd_mobilenet	2000	0.667	0.442	Batch_size=20		
_v2_fpnlite_32				Batch_norm.decay=0.98		
0_x320_coco17_tpu-8						
ssd_mobilenet	2000	0.762	0.578	Batch_size=45		
_v2_fpnlite_32				Batch_norm.decay=0.998		
0_x320_coco17_tpu-8						
ssd_mobilenet	2000	0.772	0.596	Batch_size=100		
_v2_fpnlite_32				Batch_norm.decay=0.998		
0_x320_coco17_tpu-8				Iou_threshold=0.58		
ssd_mobilenet	2000	0.633	0.317	Batch_size=100		
_v2_fpnlite_32				Batch_norm.decay=0.998		
0_x320_coco17_tpu-8				Iou_threshold=0.58		
				Learning_rate_base=0.01		
				Warmup_learning_rate=0.005		

ssd_mobilenet _v2_fpnlite_32	3000	0.794	0.645	Batch_size=50 Iou_threshold=0.58
0_x320_coco17_tpu-8				Batch_norm.decay=0.998 classification_weight=1.2
				localization_weight=1.2
ssd_mobilenet	3000	0.574	0.384	Batch_size=50
_v2_fpnlite_32				Iou_threshold=0.58
0_x320_coco17_tpu-8				Batch_norm.decay=0.998
				classification_weight=1.15
				localization_weight=1.15
ssd_mobilenet	3000	0.753	0.602	Batch_size=50
_v2_fpnlite_32				Iou_threshold=0.58
0_x320_coco17_tpu-8				Batch_norm.decay=0.998
				classification_weight=1.25
				localization_weight=1.25
ssd_mobilenet	3000	0.749	0.588	Batch_size=50
_v2_fpnlite_32				Iou_threshold=0.58
0_x320_coco17_tpu-8				Batch_norm.decay=0.998
				classification_weight=1.21
				localization_weight=1.21
ssd_mobilenet	3000	0.755	0.612	Batch_size=50
_v2_fpnlite_32				Iou_threshold=0.58
0_x320_coco17_tpu-8				Batch_norm.decay=0.998
				classification_weight=1.2
				localization_weight=1.2
				learning_rate_base=0.03
ssd_mobilenet	3000	0.772	0.621	Batch_size=50
_v2_fpnlite_32				Iou_threshold=0.58
0_x320_coco17_tpu-8				Batch_norm.decay=0.998
				classification_weight=1.2
				localization_weight=1.2
				learning_rate_base=0.02
ssd_mobilenet	3000	0.735	0.596	Batch_size=50
_v2_fpnlite_32				Iou_threshold=0.58
0_x320_coco17_tpu-8				Batch_norm.decay=0.998
				classification_weight=1.2
				localization_weight=1.2
				learning_rate_base=0.08
ssd_mobilenet	2000	0.806	0.635	
_v2_fpnlite_32				Batch_size=1
0_x320_coco17_tpu-8				
ssd_mobilenet	2000	0.864	0.730	Warmup_steps=1000
_v2_fpnlite_32				Batch_size=50
0_x320_coco17_tpu-8				
ssd_mobilenet	2500	0.806	0.644	Batch_size=50
_v2_fpnlite_64				Learning_rate_base=0.03
0_x640_coco17_tpu-8				Classification_weight=1.2
ssd_mobilenet	2500	0.808	0.652	Batch_size=32
_v2_fpnlite_64	1000	0.000	0.002	Learning_rate_base=0.03
0_x640_coco17_tpu-8				Classification_weight=1.2
				Ciassification_weight-1.2

ssd_mobilenet	2500	0.830	0.645	Batch_size=32
_v2_fpnlite_64	2000	0.000	0.040	Learning_rate_base=0.01
0_x640_coco17_tpu-8				Warmup_learning_rate=0.005
				Classification_weight=1.2
ssd_mobilenet	2500	0.879	0.707	
_v2_fpnlite_64	2300	0.079	0.707	Batch_size=75
0_x640_coco17_tpu-8				Learning_rate_base=0.01
0_X040_C0C017_tpu 8				Warmup_learning_rate=0.005
				Classification_weight=1.2
ssd_mobilenet	1500	0.775	0.229	Batch_size=30
_v2_fpnlite_32				Classification_weight=1.3
0_x320_coco17_tpu-8	0000		0.051000	1 00
ssd_mobilenet	2000	_	0.651338	Aspect_scale=3.0
_v2_fpnlite_32				
0_x320_coco17_tpu-8 ssd_mobilenet	0000		0.000001	D. 4.1
_v2_fpnlite_32	2000	_	0.696061	Batch_size=80
0_x320_coco17_tpu-8				
ssd_mobilenet	2000	_	0.707331	Learning_rate=0.025
_v2_fpnlite_32	2000	_	0.707331	Learning_rate=0.025
0_x320_coco17_tpu-8				
ssd_mobilenet	3000	0.882	0.701	Batch_size=20
_v2_fpnlite_32	0000	0.002	0.701	Classification_weight=1.1
0_x320_coco17_tpu-8				Localization_weight=1.0
0_555				Learning_rate_base=0.02
				Warmup_learning_rate=0.01
ssd_mobilenet	3000	0.860149	0.701	Batch_size=50
_v2_fpnlite_32				Classification_weight=1.1
0_x320_coco17_tpu-8				Localization_weight=1.25
ssd_mobilenet	3000	0.8797210	0.710371	Batch_size=50
_v2_fpnlite_32				Classification_weight=1.25
0_x320_coco17_tpu-8				Localization_weight=1.25
ssd_mobilenet	3000	0.873	0.697	Batch_size=32
_v2_fpnlite_32				Classification_weight=1.2
0_x320_coco17_tpu-8				
ssd_mobilenet	3000	0.808	0.602	Batch_size=32
_v2_fpnlite_32				Classification_weight=1.2
0_x320_coco17_tpu-8	0000	2 2 2 2		Learning_rate_base=0.04
ssd_mobilenet	3000	0.833	0.690	Batch_size: 32
_v2_fpnlite_32				Classification_weight=1.2
0_x320_coco17_tpu-8	0000	0.044	0.055	Learning_rate_base=0.095
ssd_mobilenet	3000	0.844	0.655	Batch_size=32
_v2_fpnlite_32				Classification_weight=1.2
0_x320_coco17_tpu-8	2000	0.964	0.710	Localization_weight=1.1
ssd_mobilenet	3000	0.864	0.712	Batch_size=32
_v2_fpnlite_32 0_x320_coco17_tpu-8				Classification_weight=1.2 Localization_weight=1.2
ssd_mobilenet	3000	0.840	0.695	Batch_size=32
_v2_fpnlite_32	3000	0.040	0.685	Classification_weight=1.2
0_x320_coco17_tpu-8				Localization_weight=1.25
0_x320_c0c017_tpu=8				Lucanzation_weight=1.20

2000	0.001	0.700	Batch_size=32
3000	0.901	0.708	_
			Classification_weight=1.25
			Localization_weight=1.25
3000	0.882	0.681	Batch_size=32
			Classification_weight=1.28
			Localization_weight=1.28
3000	0.846	0.684	Batch_size=32
			Classification_weight=1.25
			Localization_weight=1.25
			batch_norm_epsilon=0.002
3000	0.841	0.678	Batch_size=32
			Classification_weight=1.25
			Localization_weight=1.25
			batch_norm_epsilon=0.01
3000	0.839	0.660	Batch_size=32
0000	0.000	0.000	Classification_weight=1.24
			Localization_weight=1.26
			batch_norm_epsilon=0.01
3000	0.847	0.606	Batch_size=32
3000	0.047	0.030	Classification_weight=1.25
			Localization_weight=1.25
			Learning_rate_base=0.05
0000	0.041	0.074	
3000	0.841	0.674	Batch_size=32
			Classification_weight=1.3
			Localization_weight=1.3
			Learning_rate_base=0.05
3500	0.836	0.679	Batch_size=50
			Classification_weight=1.5
			Localization_weight=1.5
3500	0.810	0.642	Batch_size=50
			Classification_weight=1.25
			Localization_weight=1.25
3500	0.886	0.723	Batch_size=50
			Classification_weight=1.2
			Localization_weight=1.2
	3000 3000 3000 3500	3000 0.882 3000 0.846 3000 0.841 3000 0.839 3000 0.847 3000 0.841 3500 0.836	3000 0.882 0.681 3000 0.846 0.684 3000 0.841 0.678 3000 0.839 0.660 3000 0.847 0.696 3000 0.841 0.674 3500 0.836 0.679 3500 0.810 0.642