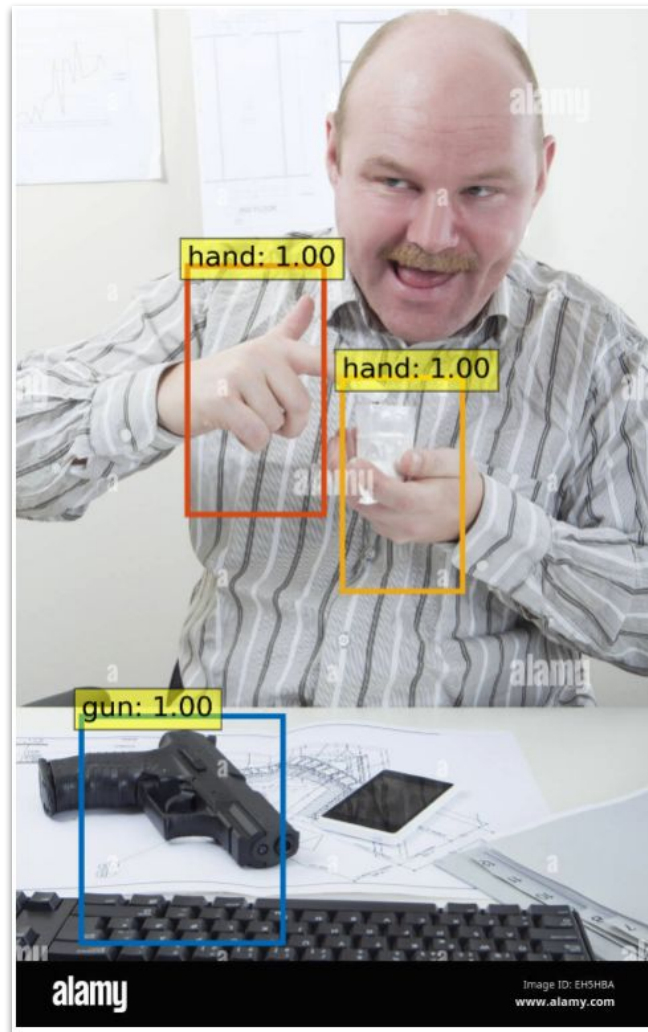


Detection Transformer For Hands, Guns and Phones

Joey Palanca | Ali Ghazy Alsharif | Marco Lorenz

Overview

1. **Problem definition: Object Detection**
2. History - Object Detection Milestones
3. DETR
 - a. Previous work: Transformer and Parallel Decoding
 - b. Object Detection Set Prediction Loss
 - c. Architecture
 - d. HGP-Dataset
4. Results: Hyperparameter Study
5. Live Demo



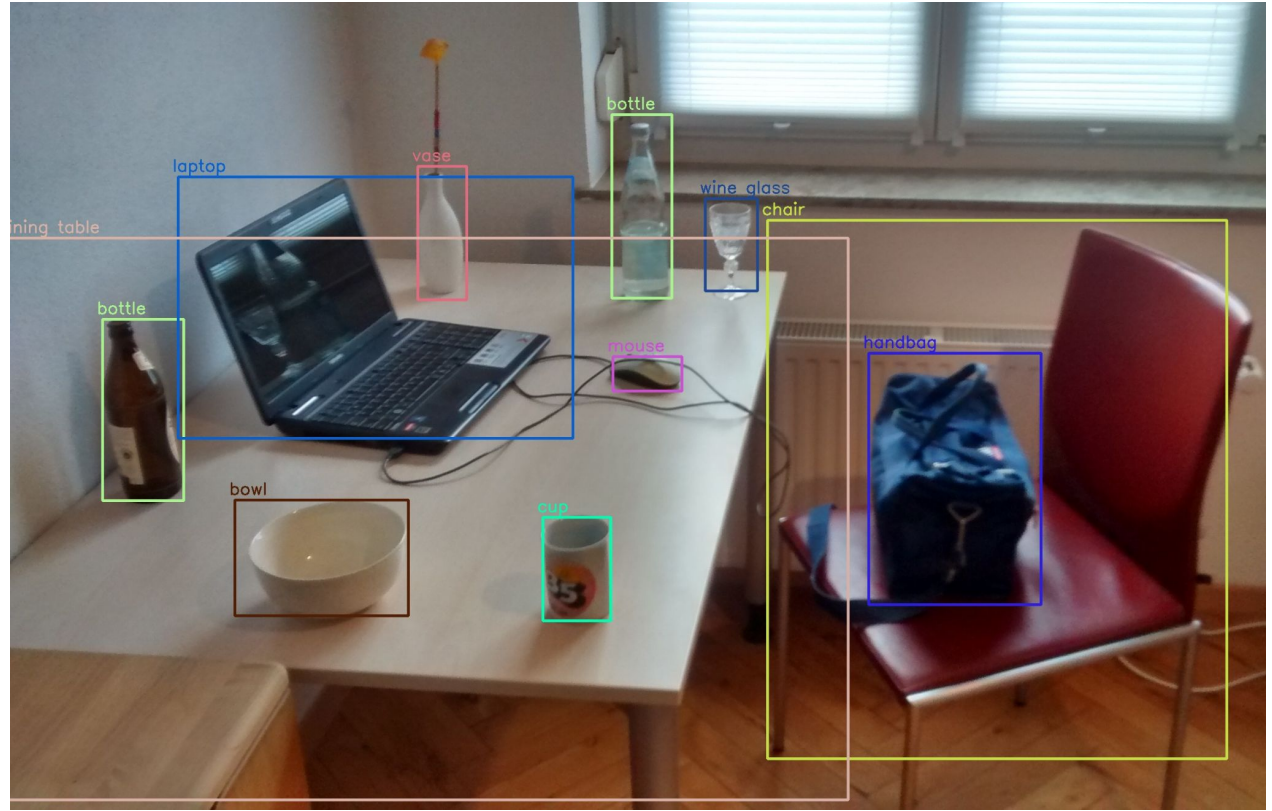
Object Detection

Detecting instances of **semantic objects** of a certain **class** (such as humans, cars, tools) in photos and videos by predicting

- **Object class**
- **Bounding box**

Applications:

- Autonomous Driving
- Robotics
- Image Retrieval
- Video Surveillance
- etc...



Object Detection - History

Object Detection Milestones

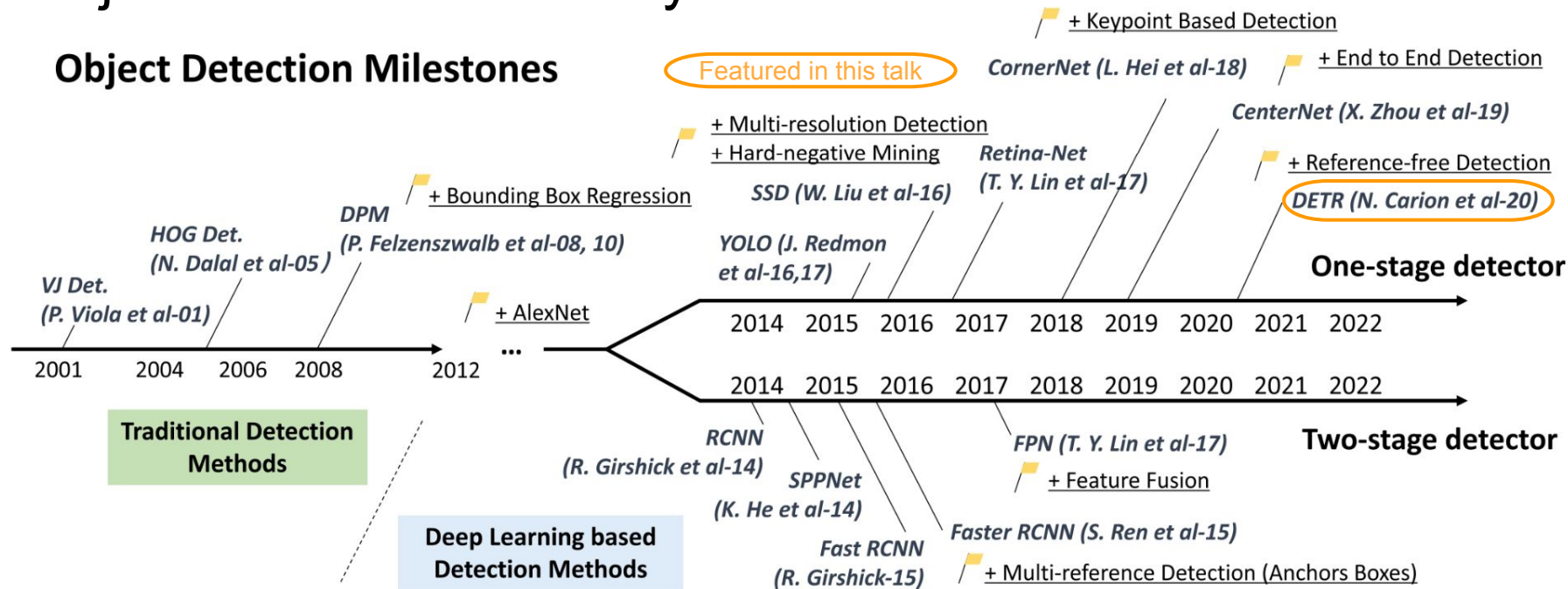


Fig. 2. Road map of object detection. Milestone detectors in this figure: VJ Det. [10], [11], HOG Det. [12], DPM [13], [14], [15], RCNN [16], SPPNet [17], Fast RCNN [18], Faster RCNN [19], YOLO [20], [21], [22], SSD [23], FPN [24], Retina-Net [25], CornerNet [26], CenterNet [27], and DETR [28].

DETR - Object Detection as Direct Set Prediction Problem

Main innovations:

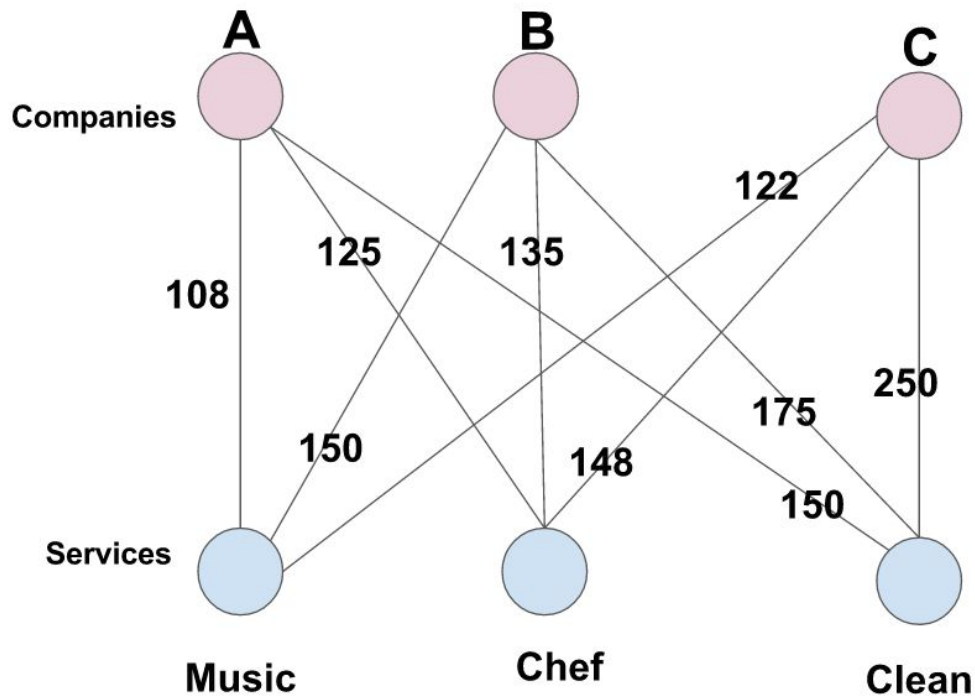
Set-based global loss forcing unique predictions

AND

Transformer encoder-decoder architecture applied to Object Detection

- **Cutting off** hand-designed components based on **prior knowledge** like non-maximum suppression or anchor generation
- Accuracy and run-time performance on par with highly optimized Faster R-CNN, indicating future potential (Deformable DETR, Swin Transformer)

Object detection set prediction loss - Introduction



In the context of DETR:

- Services: Set of predictions
- Companies: Set of ground truth labels and bounding boxes (padded with “no-object” labels)
- Weights: Custom cost function computed for each set of predictions

Object detection set prediction loss - Overview

Two-Step Approach:

1. Compute **optimal assignment** with *Hungarian algorithm*
→ Criterion: Pairwise matching cost w.r.t. class AND bounding box
2. With optimal assignment, compute the *Hungarian loss function to optimize for*



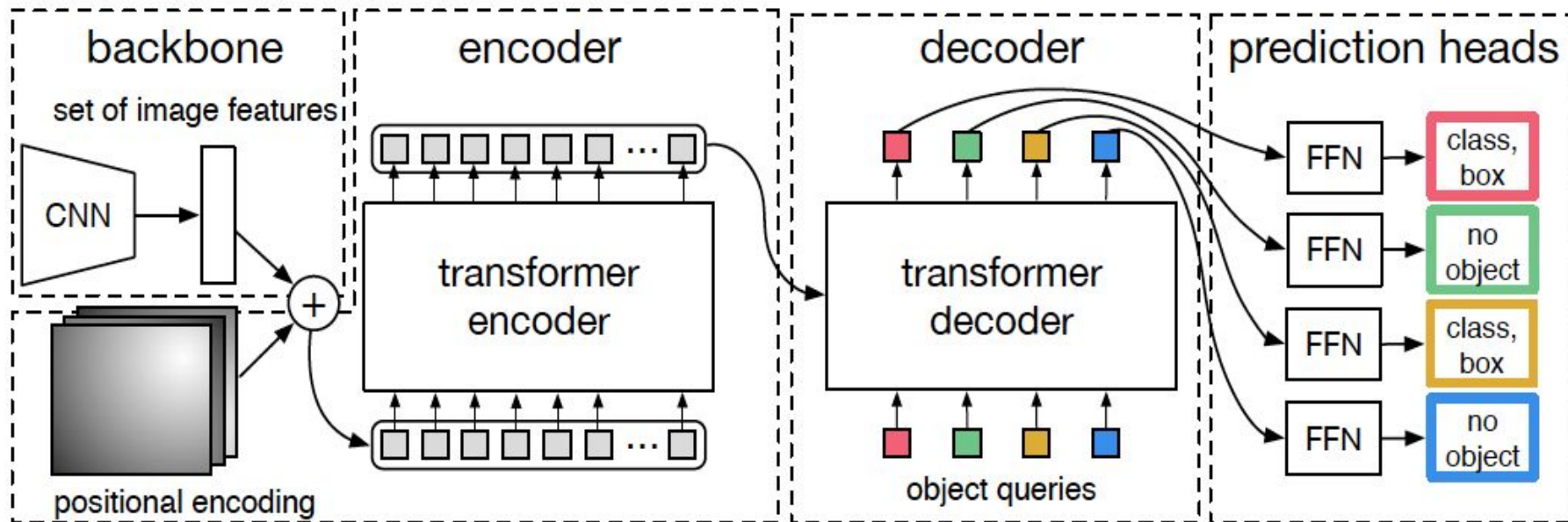
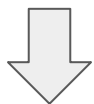
Hungarian loss - Putting it all together

*Fixed size N of
prediction set*

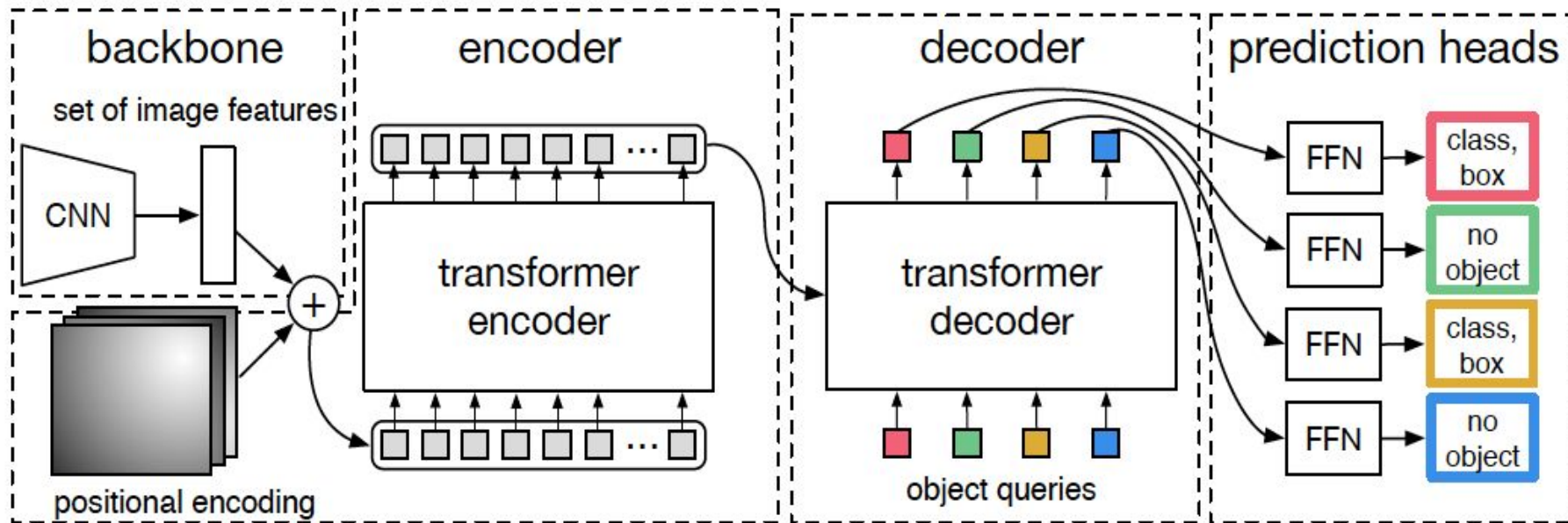
$$\mathcal{L}_{\text{Hungarian}}(y, \hat{y}) = \sum_{i=1}^N \left[-\log \hat{p}_{\hat{\sigma}(i)}(c_i) + \mathbb{1}_{\{c_i \neq \emptyset\}} \mathcal{L}_{\text{box}}(b_i, \hat{b}_{\hat{\sigma}(i)}) \right]$$

*Optimal assignment
computed in step 1*

DETR Architecture - Overview



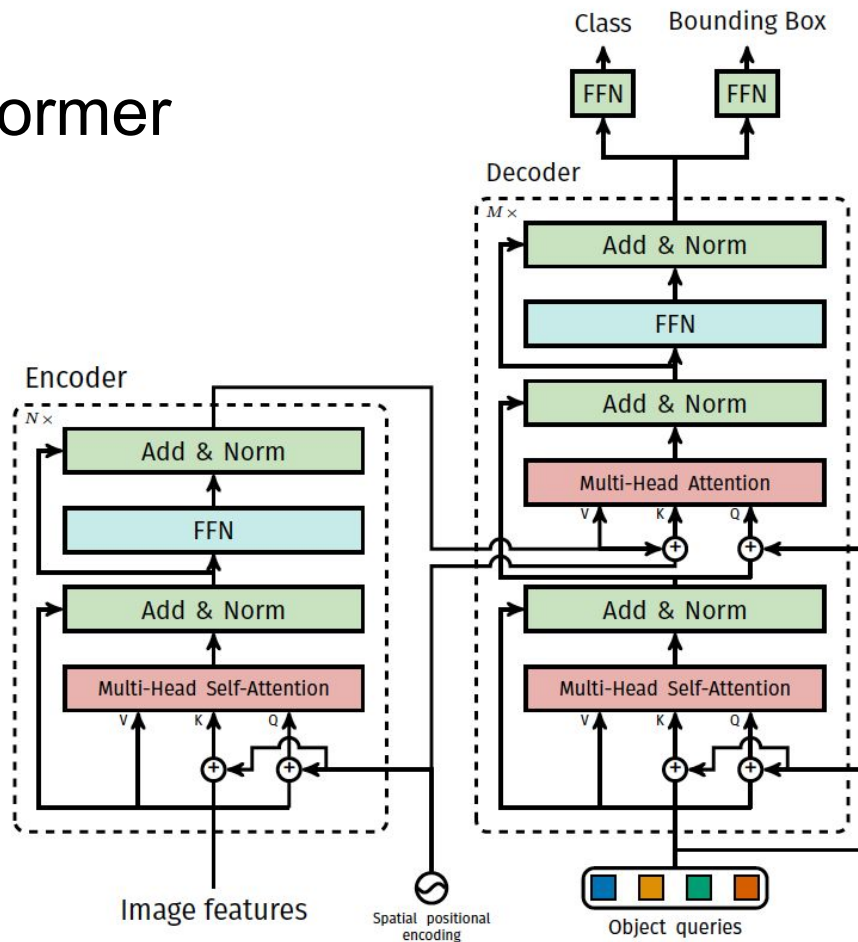
DETR Architecture - Overview



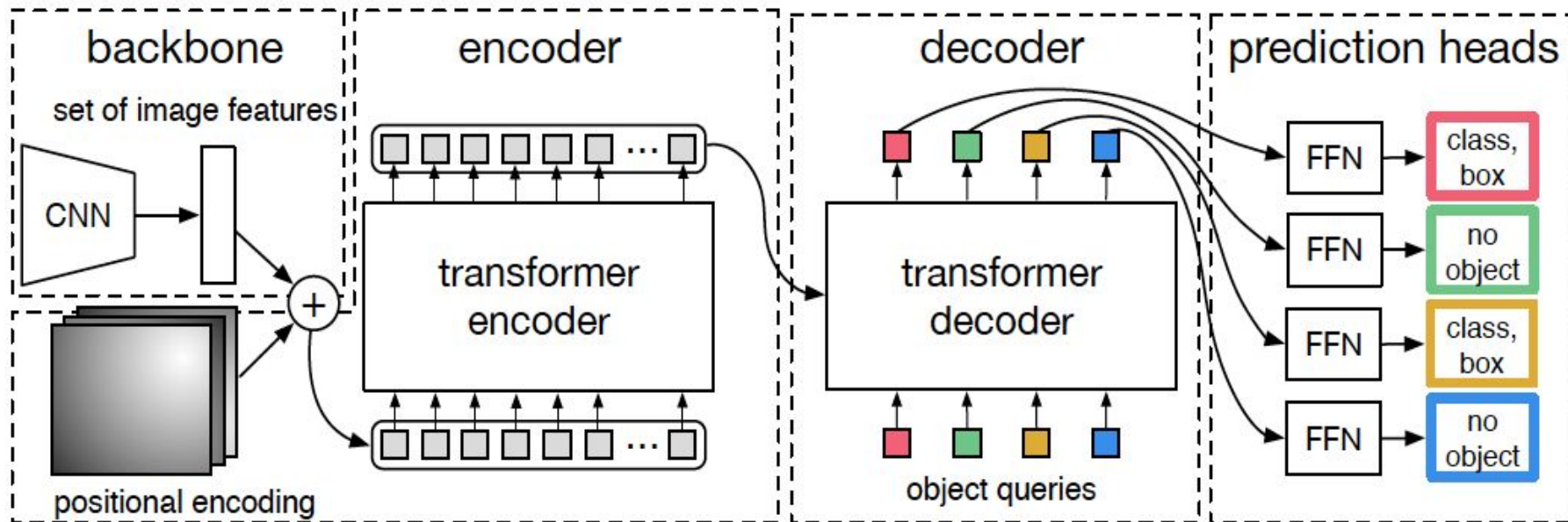
DETR Architecture - Transformer Encoder-Decoder

Main differences to original transformer (Vaswani et al., 2017):

- Input: Convolutional feature map instead of word-embeddings
- **Spatial** positional encodings
- **Fixed size** set of Object Queries
- **Parallel decoding** of N object queries as opposed to auto-regressive one-by-one prediction of variable-length output sequence



DETR Architecture - Overview



DETR Architecture - PyTorch

```
class DETR(nn.Module):
    def forward(self, samples: NestedTensor):
        """The forward expects a NestedTensor, which consists of: ...
        if isinstance(samples, (list, torch.Tensor)):
            samples = nested_tensor_from_tensor_list(samples)
        with annotate("forward_backbone"): # Added by Marco Lorenz on April 8th, 2024
            features, pos = self.backbone(samples)

            src, mask = features[-1].decompose()
            assert mask is not None
            with annotate("forward_transformer"): # Added by Marco Lorenz on April 8th, 2024
                hs = self.transformer(self.input_proj(src), mask, self.query_embed.weight, pos[-1])[0]

            with annotate("forward_output_classes"): # Added by Marco Lorenz on April 8th, 2024
                outputs_class = self.class_embed(hs)
            with annotate("forward_output_boxes"): # Added by Marco Lorenz on April 8th, 2024
                outputs_coord = self.bbox_embed(hs).sigmoid()
            out = {'pred_logits': outputs_class[-1], 'pred_boxes': outputs_coord[-1]}
            if self.aux_loss:
                out['aux_outputs'] = self._set_aux_loss(outputs_class, outputs_coord)
            return out
```

COCO vs HGP

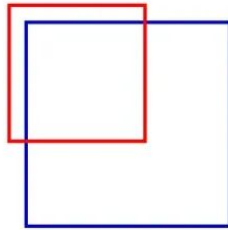
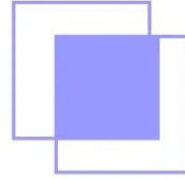
- COCO (Common Objects in Context): Huge Dataset, rich API
 - Large-scale image recognition dataset
 - For object detection, segmentation, and captioning tasks
 - **330,000 images**, each annotated with **80 object categories** and 5 captions describing the scene
 - Sponsored by Microsoft, Meta, etc
- HGP (Hands, Guns and Phones) Dataset: Small Dataset, not so rich API
 - **1199 images** (1989 for training and 210 for testing): about 1:10
 - People using guns or phones in real-world scenarios (people making phones reviews, shooting drills, or making calls)
 - Labeled with the bounding boxes of Hands, Phones and Guns
 - Collected from Youtube videos, with different sizes.

HGP Dataset - Implementation of VisionDataset (PyTorch)

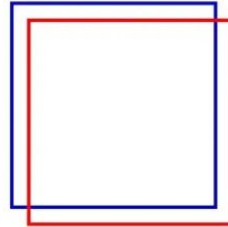
```
31 class HGPDetection(VisionDataset):
32 >     def __init__(self, img_folder: str, lab_folder: str, ann_file: str, image_set: str, transforms): ...
42
43 >     def _load_image(self, id: int) -> Image.Image: ...
46
47 >     def _load_target(self, id: int) -> List[Any]: ...
49
50     def __getitem__(self, index: int) -> Tuple[Any, Any]:
51         image_id = self.ids[index]
52         image = self._load_image(index)
53         target = self._load_target(index)
54
55         target = {'image_id': image_id, 'annotations': target}
56         image, target = self.prepare(image, target)
57         if self._transforms is not None:
58             image, target = self._transforms(image, target)
59
60         return image, target
61
62     def __len__(self) -> int:
63         return len(self.ids)
```

Precision Metric - Intersection over Union

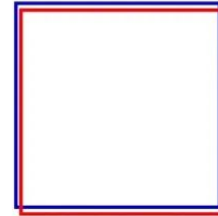
$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$



Poor



Good



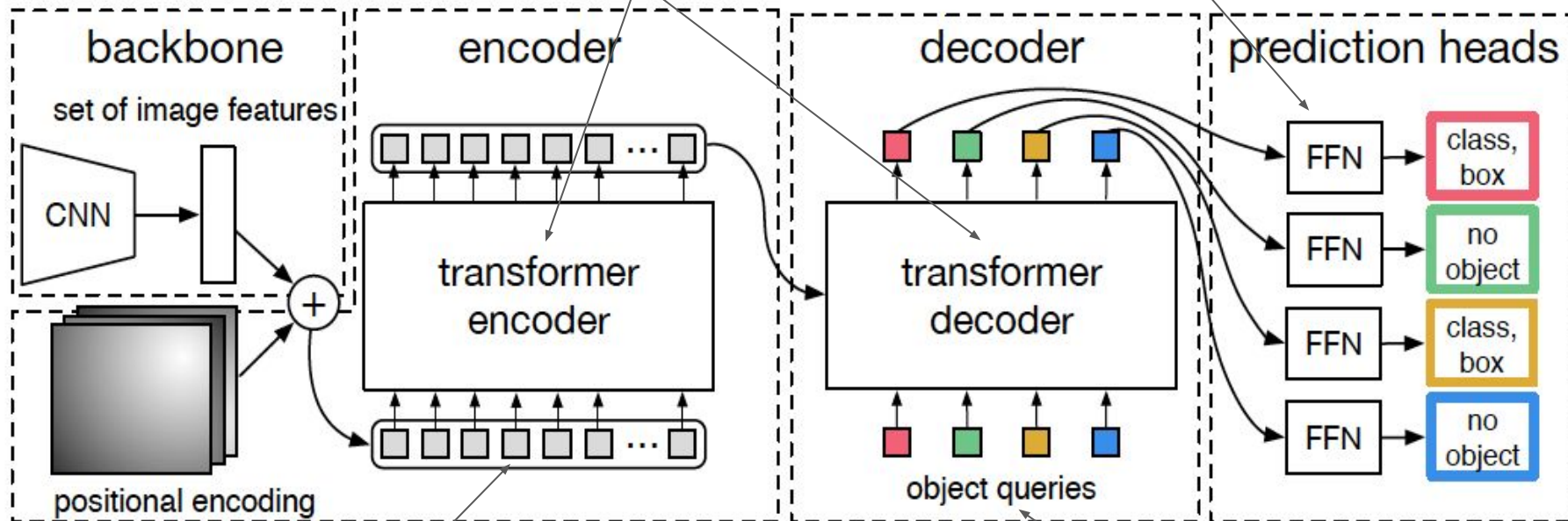
Excellent

Hyperparameters

1. Batch Size

3. Feedforward dimension

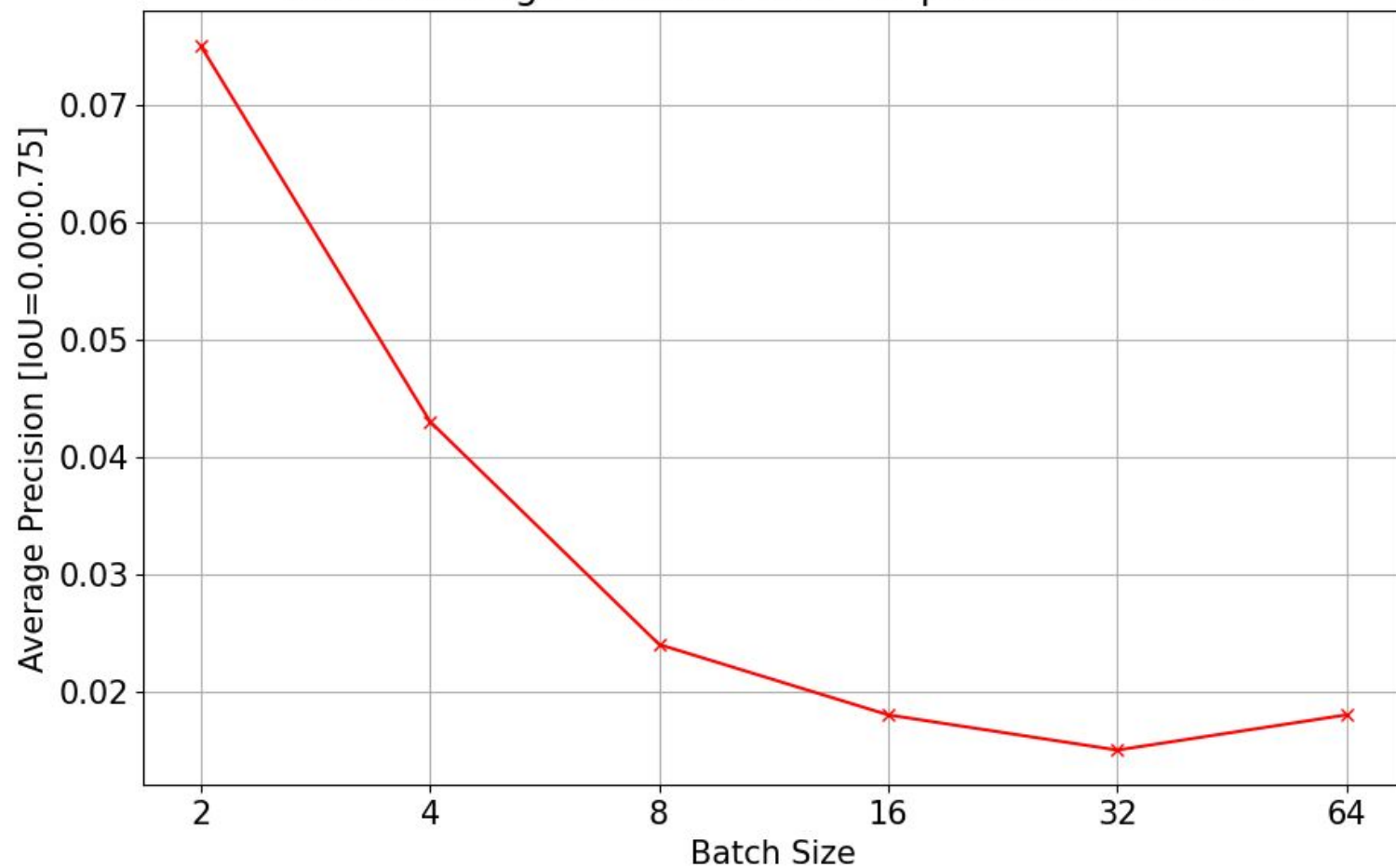
5. #Attention Heads



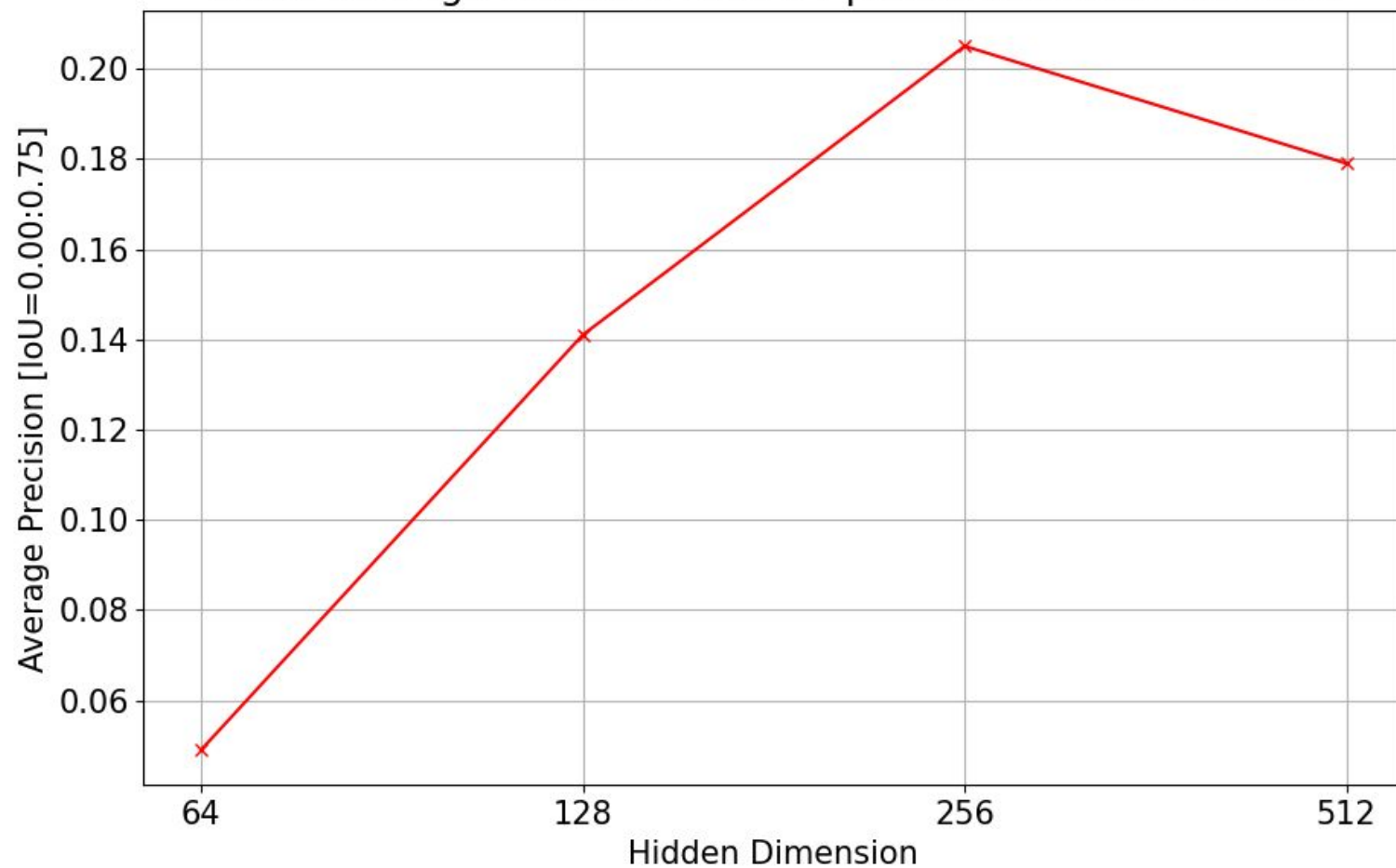
2. Hidden dimension

4. Number of Queries

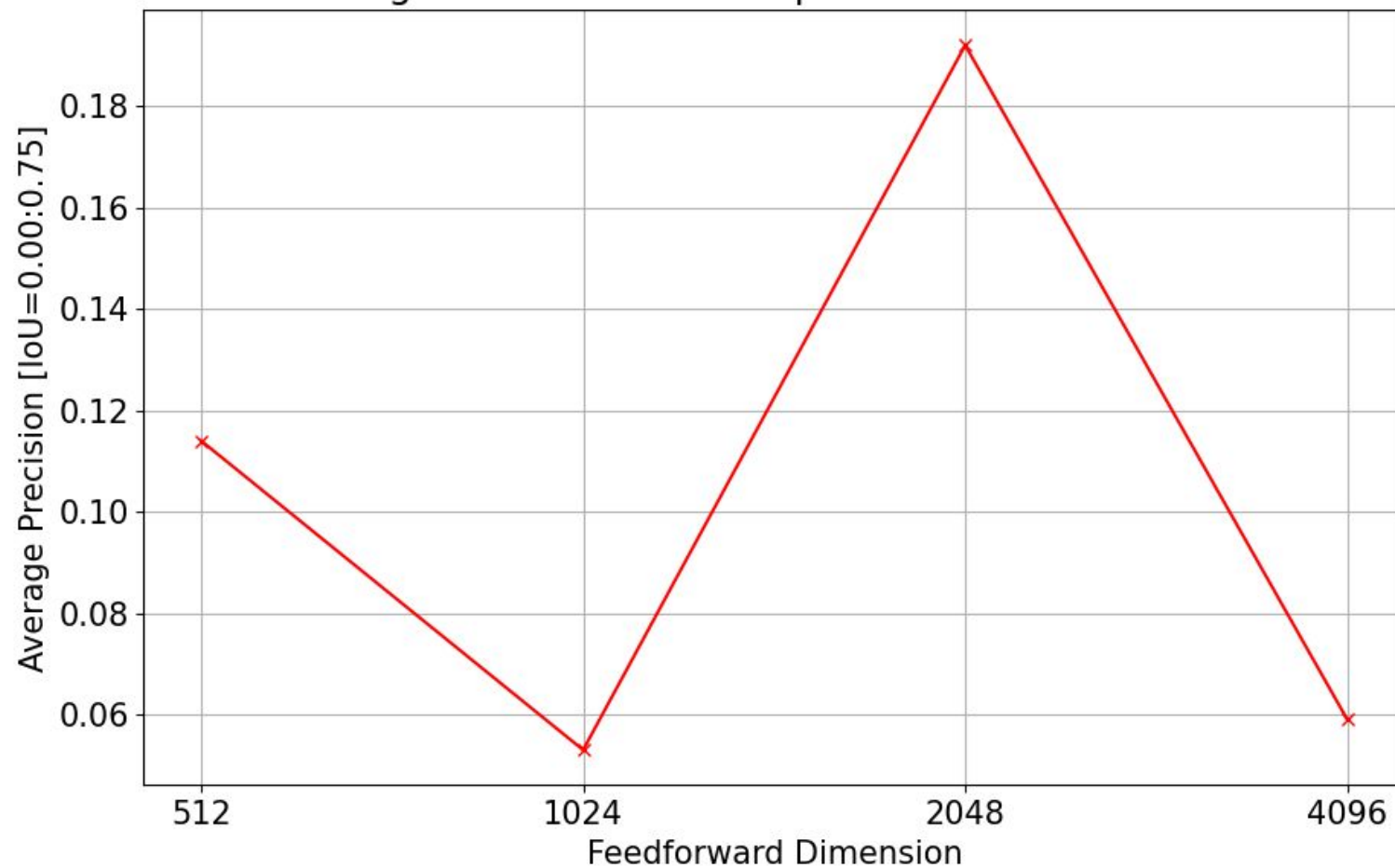
DETR Average Precision after 3 Epochs: Batch Size



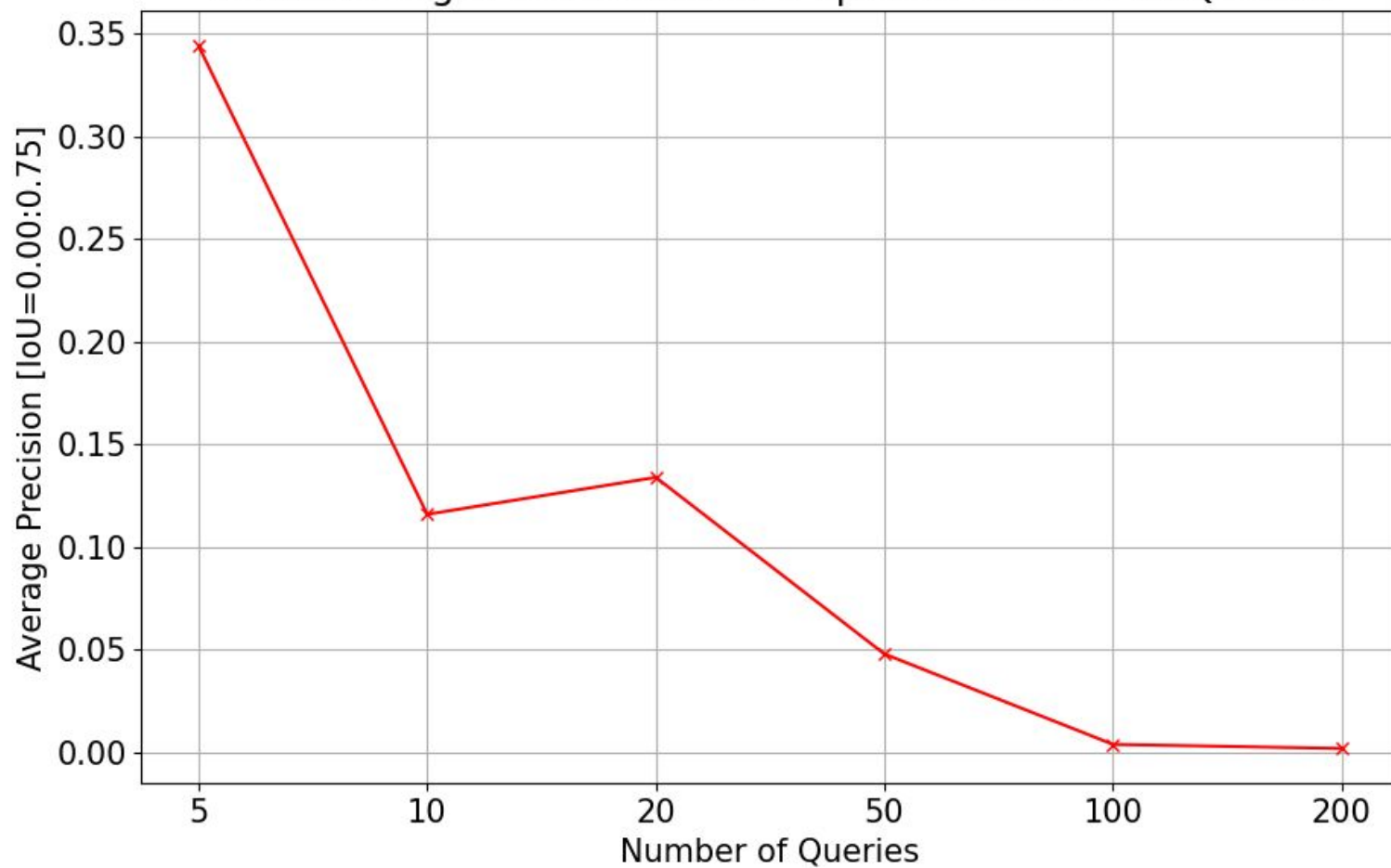
DETR Average Precision after 3 Epochs: Hidden Dimension



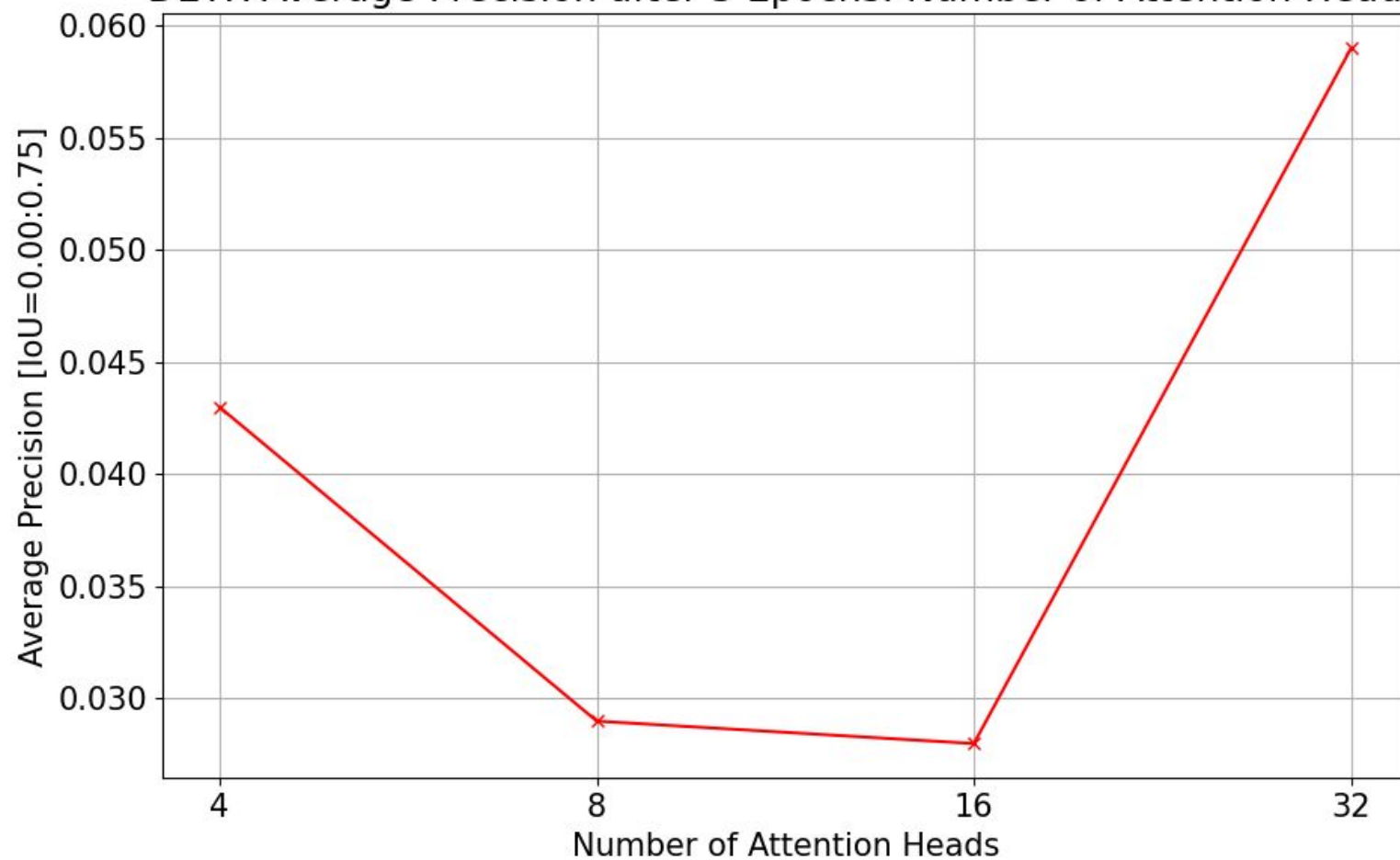
DETR Average Precision after 3 Epochs: Feedforward Dimension



DETR Average Precision after 3 Epochs: Number of Queries



DETR Average Precision after 3 Epochs: Number of Attention Heads



Live-Demo

References

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[3] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin. Attention is all you need, 2023.

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