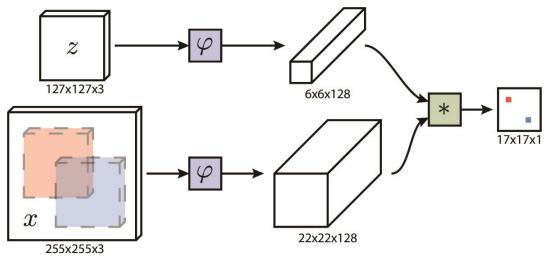
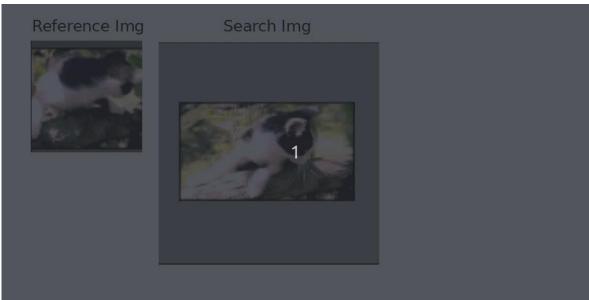
# SiamFC Tracker Comparison from multiple perspectives

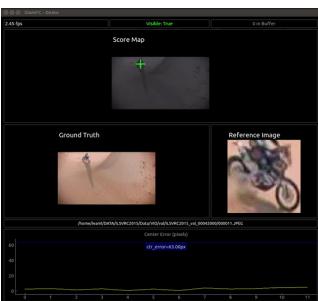
# SiamFC Tracker Comparison from multiple perspectives

- 1. Backbone network
- 2. Training dataset
- 3. Loss function
- 4. Optimizer

### SiamFC(Fully-Convolutional Siamese Networks for Object Tracking)

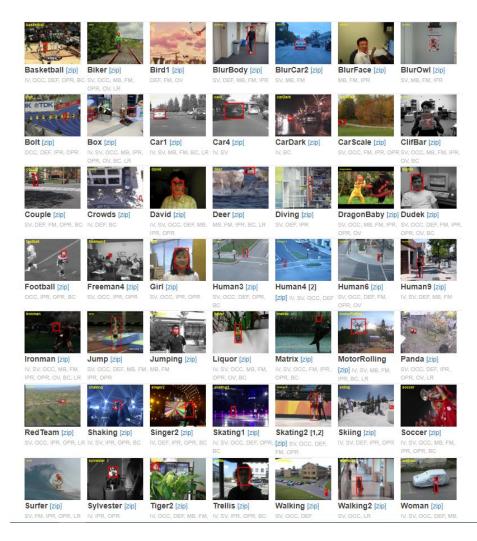


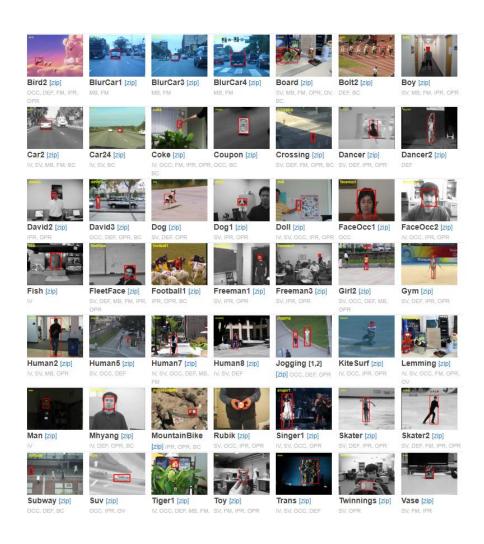




### **Test Dataset:**

# OTB2015 : Object Tracking Benchmark(2015) 100 sequences

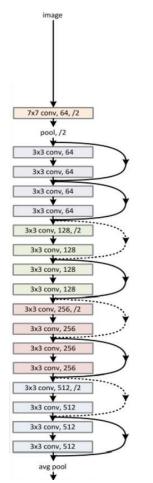




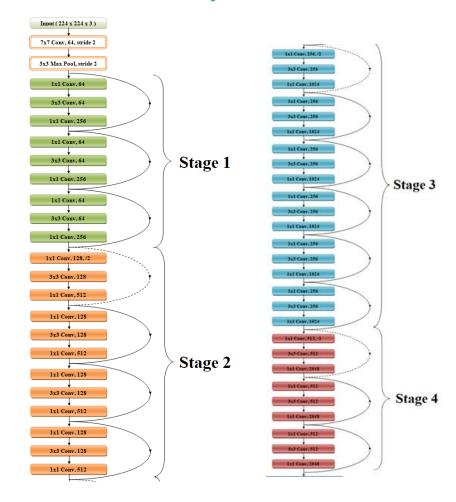
# **Comparison Backbone Network**

#### Backbone network details

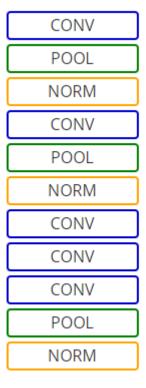
#### Residual Network 18-layer



#### Residual Network 50-layer

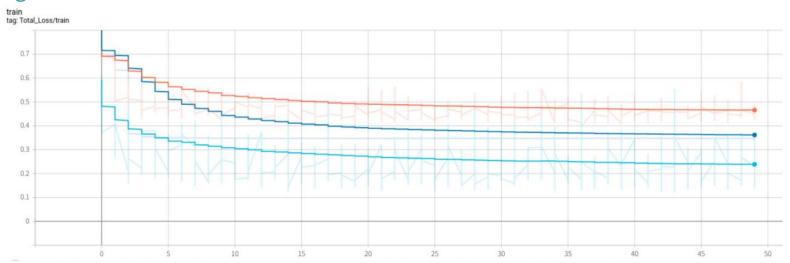


#### **Alex Network**



# **Comparison Backbone Network**

#### **Learning Curve**



Orange: ResidualNet-18
Blue: ResidualNet-50
Light Blue: AlexNet

#### **Performance**

	Res-18	Res-50	AlexNet
Precision	Cannot track due to lack of memory	Cannot track due to lack of memory	0.788
Success rate	Cannot track due to lack of memory	Cannot track due to lack of memory	0.593

Training Dataset: Got-10k

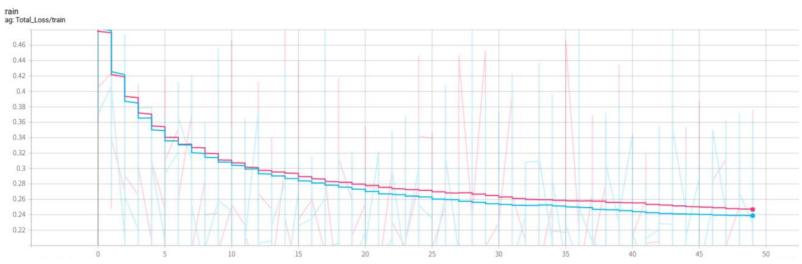
Loss Function: Balanced Cross Entropy Loss

Optimizer: SGD-Momentum

Success rate : Average success rate for each threshold. Succeed if IoU is above the threshold. (threshold = 0.6)

# **Comparison training datasets**

#### **Learning Curve**



Red: ImageNet-VID

Blue: Got-10k

#### **Performance**

	ImageNet-VID	Got-10k
Precision	0.739	0.788
Success rate	0.547	0.593

Backbone Network (feature detection): AlexNet Loss Function: Balanced Cross Entropy Loss

Optimizer: SGD-Momentum

**Success rate**: Average success rate for each threshold. Succeed if IoU is above the threshold. (threshold = 0.6)

### **Comparison LossFunction**

### **Loss Function details**

### Binary Cross Entropy Loss

$$ext{CE}(p_t) = - ext{log}(p_t).$$
  $p_t = \left\{egin{array}{ll} p & ext{if } y = 1 \ 1 - p & ext{otherwise.} \end{array}
ight.$ 

#### Focal Loss

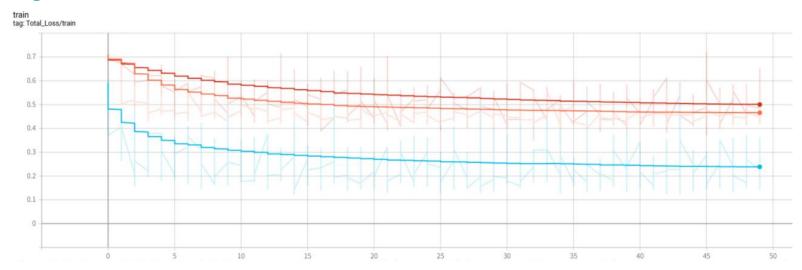
$$\mathrm{FL}(p_t) = -(1-p_t)^{\gamma} \log(p_t).$$

#### Balanced Cross Entropy Loss

$$CB_{\text{sigmoid}}(\mathbf{z}, y) = -\frac{1 - \beta}{1 - \beta^{n_y}} \sum_{i=1}^{C} \log \left( \frac{1}{1 + \exp(-z_i^t)} \right)$$

# **Comparison LossFunction**

#### **Learning Curve**



Red: Cross Entropy Loss

Orange: Focal Loss

Light Blue: Balanced Cross Entropy Loss

#### **Performance**

	CrossEntropy	Focal	BalancedCE
Precision	0.691	0.756	0.788
Success rate	0.511	0.569	0.593

Backbone Network (feature detection) : AlexNet

Training Dataset: Got-10k Optimizer: SGD-Momentum **Success rate**: Average success rate for each threshold. Succeed if IoU is above the threshold. (threshold = 0.6)

# **Comparison Optimizer**

### **Optimizer**

1. SGD (Stochastic Gradient Decent: 確率的勾配降下法)

$$W \leftarrow W \text{-} \eta \frac{\partial L}{\partial W}$$

(W:パラメータ、η:学習率、L:損失関数、dL/dW:勾配)

#### 2. Momentum

$$v \leftarrow \alpha v \text{--} \eta \frac{\partial L}{\partial W}$$

$$W \leftarrow W + v$$

### 3. Adam (Adaptive Moment Estimation)

$$m \leftarrow eta_1 m + (1 ext{-}eta_1) rac{\partial L}{\partial W}$$

$$v \leftarrow eta_2 v + (1 - eta_2) igg(rac{\partial L}{\partial W}igg)^2$$

$$\hat{v} = rac{v}{1 - eta_2}$$

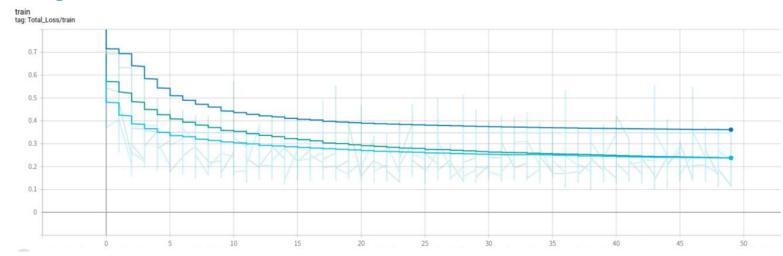
$$\hat{m} = \frac{m}{1-\beta_1}$$

$$W \leftarrow W - rac{\eta \hat{m}}{\sqrt{\hat{v} + \epsilon}}$$

1 torch.optim.Adam(params, lr=0.001, betas=(0.9, 0.999), eps=1e-08, weight\_decay=0, amsgrad=False)

# **Comparison Optimizer**

#### **Learning Curve**



Blue: SGD(No momentum)

Green: Adam

Light Blue: SGD(Momentum)

#### **Performance**

	SGD	Adam	Momentum
Precision	0.732	0.773	0.788
Success rate	0.543	0.575	0.593

Backbone Network (feature detection) : AlexNet

Training Dataset: Got-10k
Loss function: Balanced CE loss

**Success rate**: Average success rate for each threshold. Succeed if IoU is above the threshold. (threshold = 0.6)

### **Conclusion and Discussion**

### Backbone network:

• "SiamFC" is a structure that trains a similarity score map between the target image and the search image by convolution it with the target image against the search image.

So using a <u>deep layered network like ResNet</u> as a Backbone is <u>not a good match</u> due to the **increased number of dimensions and weight parameters**.

#### **Loss function:**

· Class Balanced Cross entropy loss gave the best results.

There was also an example of a combination of Focal loss and Class Balance loss, which I would like to try.

### **Optimizer**:

• The results using <u>Momentum as an optimizer were the best</u>, but we believe that adjusting Adam's hyperparameters would give better results. However, it is difficult to optimize Adam's hyperparameters because of the long training time per session.

