# <u>LambdaNetworks: Modeling long-range</u> <u>Interactions without Attention</u>

Anonymous authors
Paper under double-blind review

#### Outline

- Introduction
- Methodology
- Experiments
- Conclusion

#### Introduction

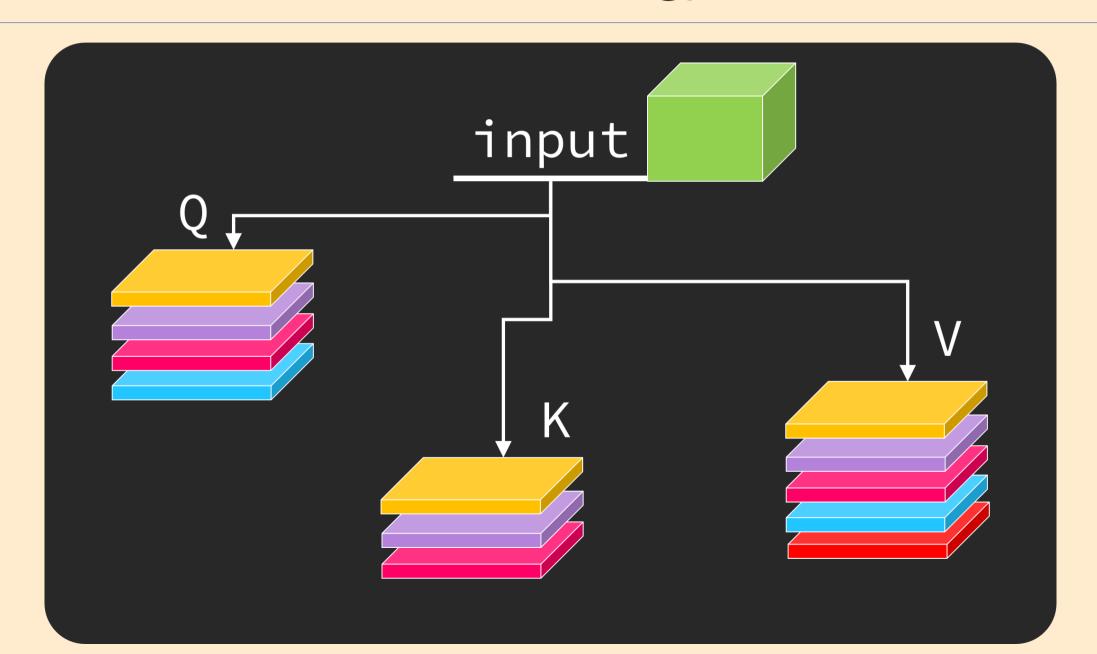
Using Self Attention to obtain contextual information is indeed helpful to improve the accuracy of the model.

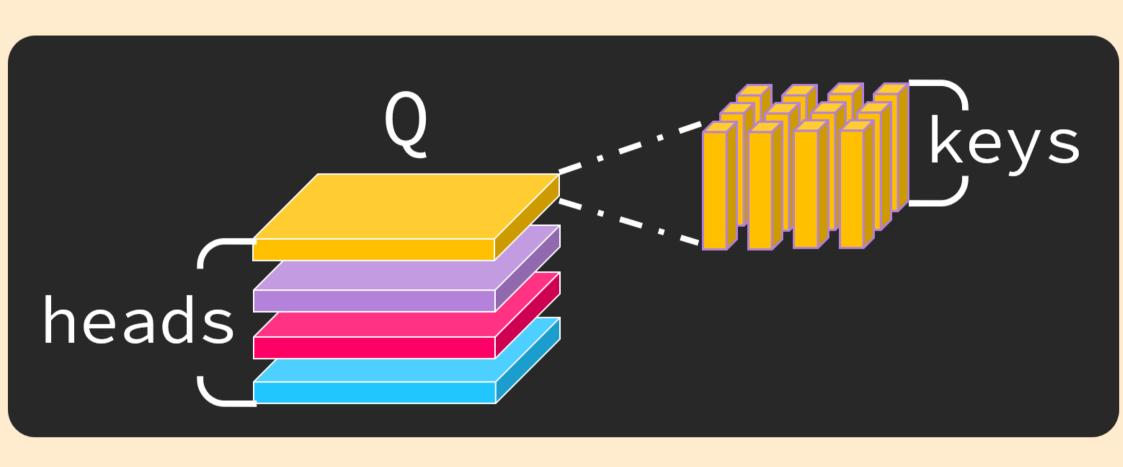
However, the amount of memory to be consumed makes it difficult to apply to very long sequences and multi-dimensional (such as images) tasks.

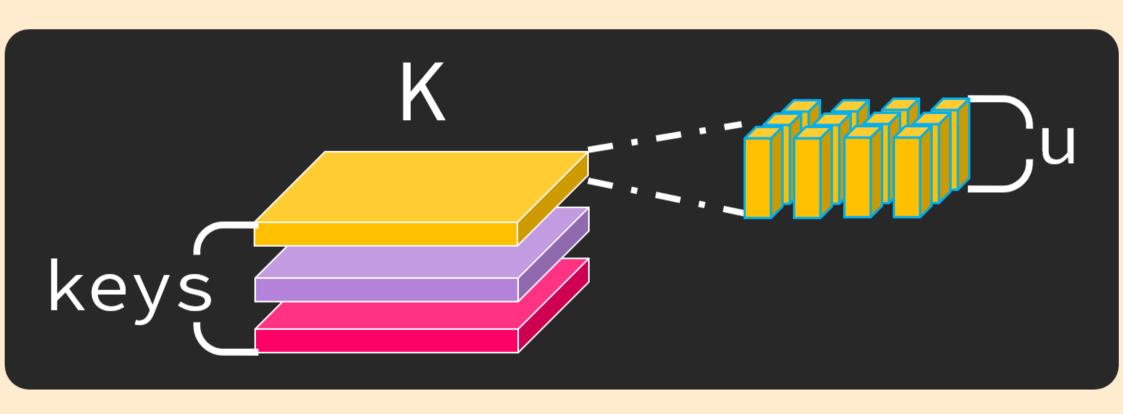
#### Introduction

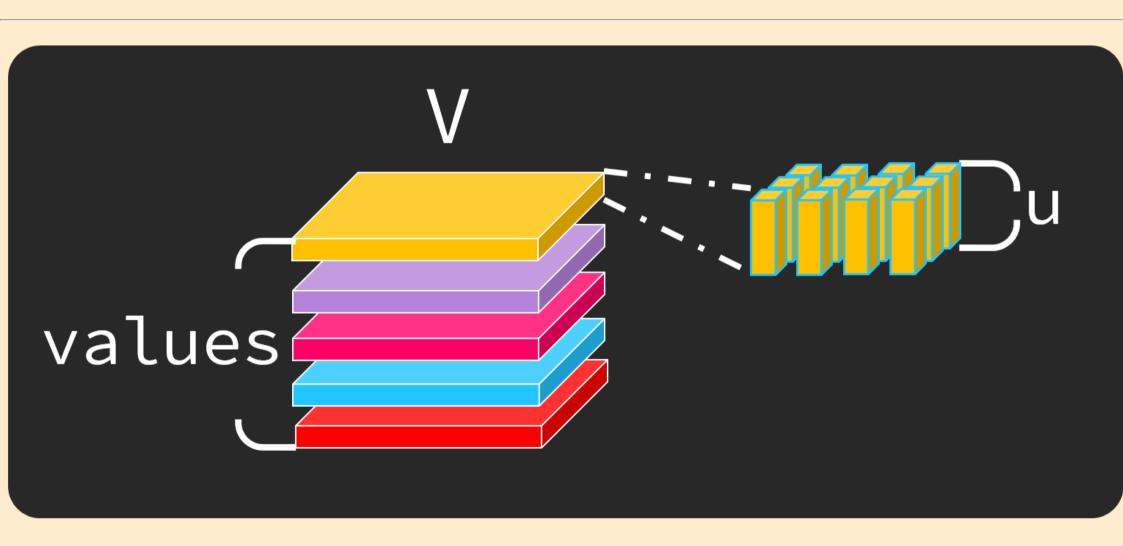
Therefore, the author proposes the architecture of lambda network, which can obtain contextual information while reducing memory consumption and increasing computing speed.

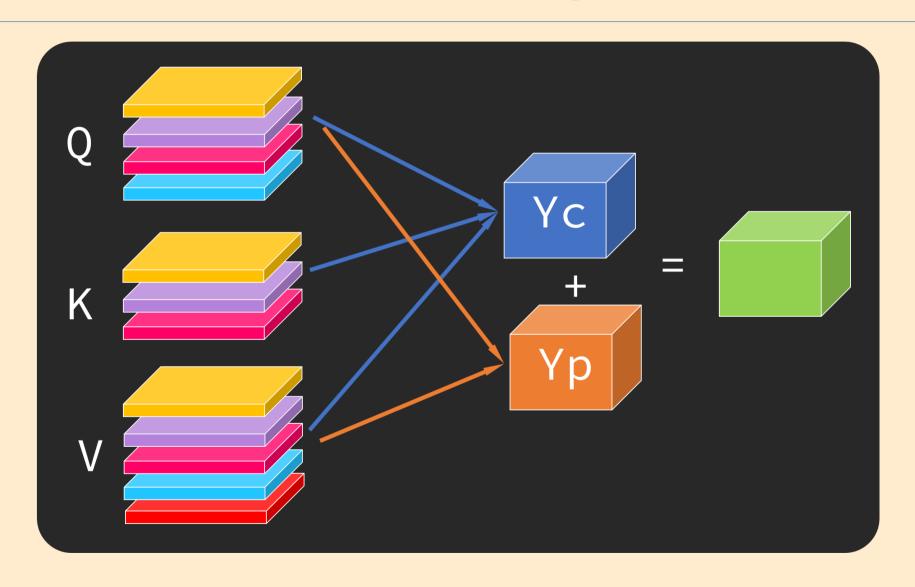
Content Lambda + Position Lambda



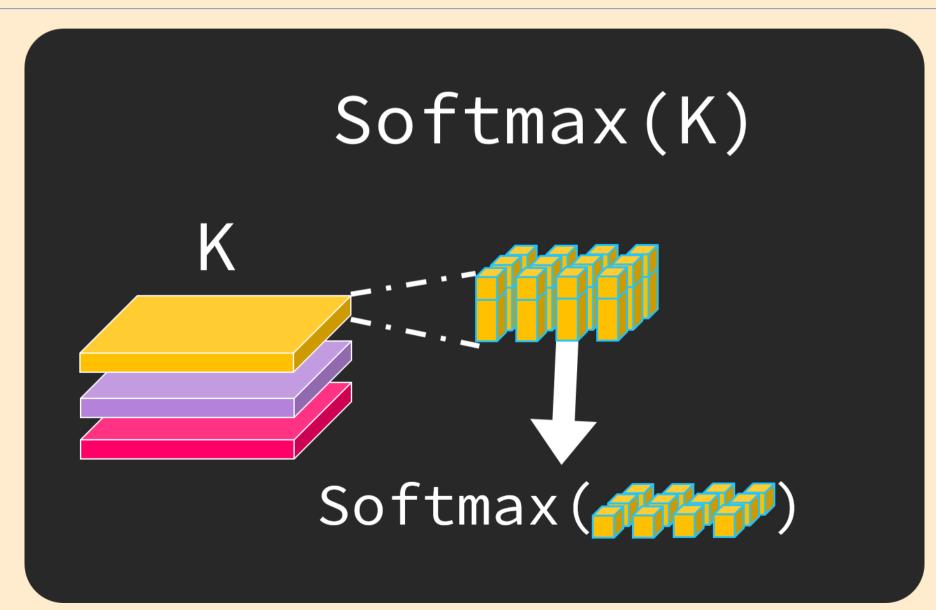


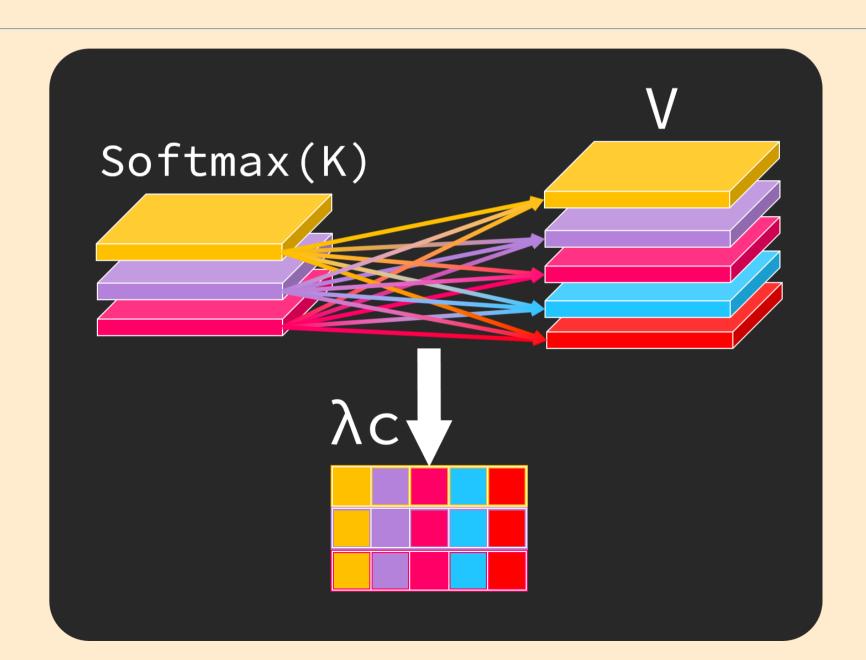


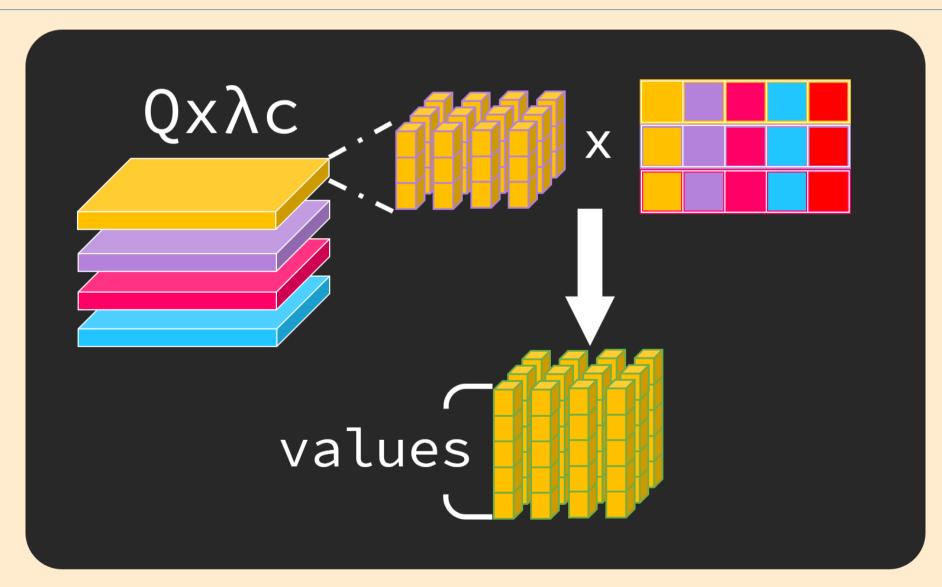


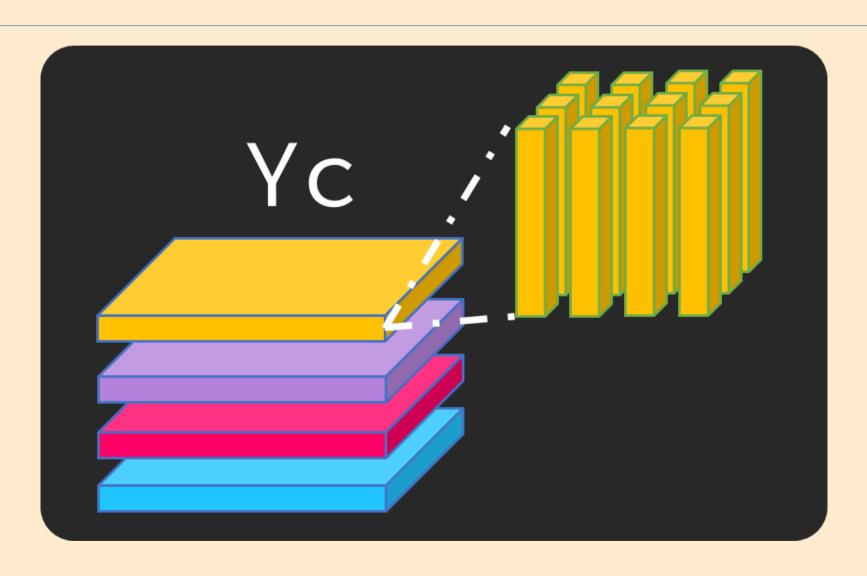


Matching to Feature [Map]

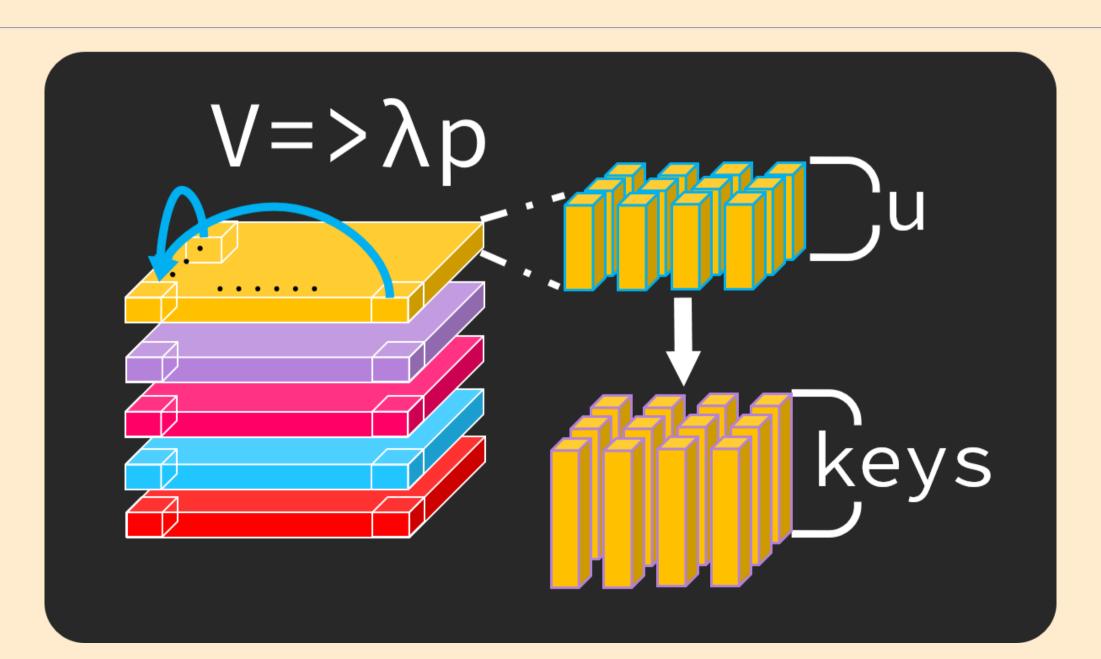


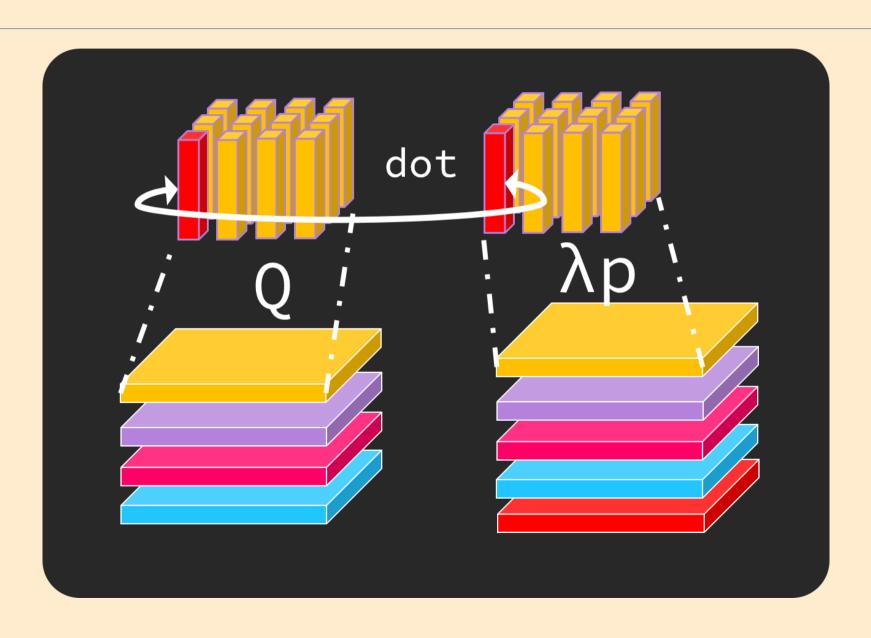


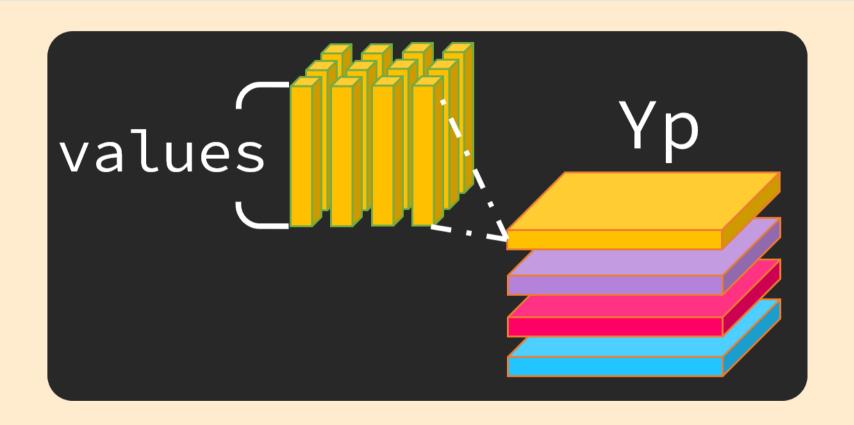




Matching to Feature [Vector]







# Experiments

- vs Baseline
- Content vs Position
- Normalization
- Other

#### Experiments

## Classification vs Baseline

Layer	Params (M)	top-1
Conv (He et al., 2016) <sup>†</sup>	25.6	$76.9_{+0.0}$
Conv + channel attention (Hu et al., 2018b) <sup>†</sup>	28.1	$77.6_{+0.7}$
Conv + linear attention (Chen et al., 2018) Conv + linear attention (Shen et al., 2018) Conv + relative self-attention (Bello et al., 2019)	33.0 - 25.8	$77.0 \\ 77.3_{+1.2} \\ 77.7_{+1.3}$
Local relative self-attention (Ramachandran et al., 2019) Local relative self-attention (Hu et al., 2019) Local relative self-attention (Zhao et al., 2020)	18.0 23.3 20.5	$77.4_{+0.5} 77.3_{+1.0} 78.2_{+1.3}$
Lambda layer ( $ u $ =4)	15.0 16.0	<b>78.4</b> <sub>+1.5</sub> <b>78.9</b> <sub>+2.0</sub>

## Detection

vs Baseline

Backbone	$AP^{bb}_{coco}$	${ m AP}^{bb}_{s/m/l}$
ResNet-101	48.2	29.9 / 50.9 / 64.9
ResNet-101 + SE	48.5	29.9 / 51.5 / 65.3
LambdaResNet-101	<b>49.4</b>	31.7 / 52.2 / 65.6
ResNet-152	48.9	29.9 / 51.8 / 66.0
ResNet-152 + SE	49.4	30.0 / 52.3 / 66.7
LambdaResNet-152	<b>50.0</b>	<b>31.8</b> / <b>53.4</b> / <b>67.0</b>

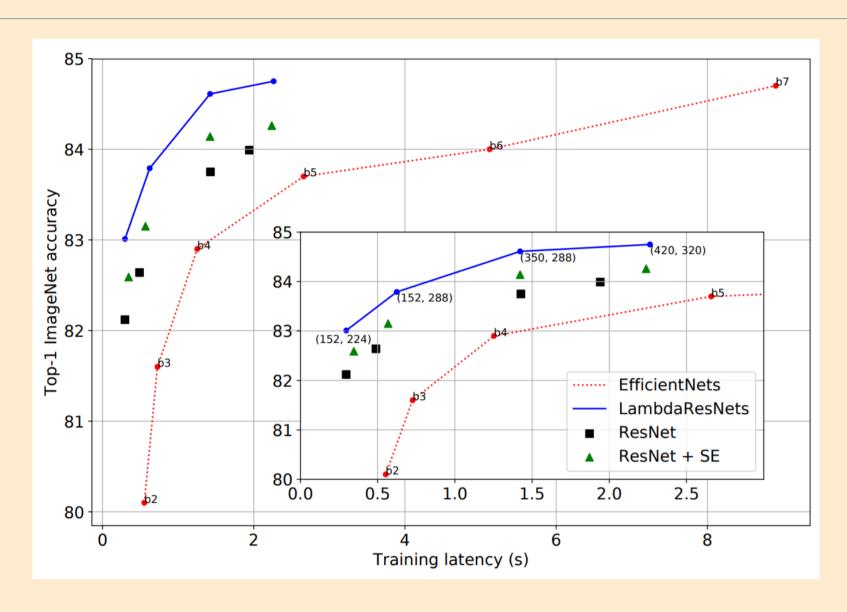
# Segmentation

vs Baseline

Backbone	$AP^{mask}_{coco}$	$\mathrm{AP}^{mask}_{s/m/l}$
ResNet-101	42.6	24.2 / 45.6 / 60.0
ResNet-101 + SE	42.8	24.0 / 46.0 / 60.2
LambdaResNet-101	<b>43.5</b>	25.9 / 46.5 / 60.8
ResNet-152	43.2	24.2 / 46.1 / 61.2
ResNet-152 + SE	43.5	24.6 / 46.8 / 61.8
LambdaResNet-152	<b>43.9</b>	25.5 / 47.3 / 62.0

# Training

#### vs Baseline



Experiments

#### Content vs Position

Content	Position	Params (M)	FLOPS (B)	top-1
$\checkmark$	×	14.9	5.0	68.8
×	$\checkmark$	14.9	11.9	78.1
	$\checkmark$	14.9	12.0	78.4

Position Lambda is more important than Content Lambda.

Experiments

#### Normalization

Normalization	top-1
Softmax on keys (default)	78.4
Softmax on keys and queries	78.1
L2-normalized keys	78.0
Non-normalized keys	70.0
No batch normalization on queries and values	76.2

It is necessary to regulate K.

#### **Other**

Architecture	Params (M)	Throughput	top-1
$\begin{array}{c} \textbf{C} \rightarrow \textbf{C} \rightarrow \textbf{C} \rightarrow \textbf{C} \\ \textbf{L} \rightarrow \textbf{C} \rightarrow \textbf{C} \rightarrow \textbf{C} \\ \textbf{L} \rightarrow \textbf{L} \rightarrow \textbf{C} \rightarrow \textbf{C} \\ \textbf{L} \rightarrow \textbf{L} \rightarrow \textbf{C} \rightarrow \textbf{C} \end{array}$	25.6 25.5 25.0 21.7	7240ex/s 1880ex/s 1280ex/s 1160ex/s	76.9 77.3 77.2 77.8
$\begin{array}{c} \mathbf{L} \rightarrow \mathbf{L} \rightarrow \mathbf{L} \rightarrow \mathbf{C} \\ \mathbf{L} \rightarrow \mathbf{L} \rightarrow \mathbf{L} \rightarrow \mathbf{L} \\ \mathbf{C} \rightarrow \mathbf{L} \rightarrow \mathbf{L} \rightarrow \mathbf{L} \\ \mathbf{C} \rightarrow \mathbf{C} \rightarrow \mathbf{L} \rightarrow \mathbf{L} \\ \mathbf{C} \rightarrow \mathbf{C} \rightarrow \mathbf{C} \rightarrow \mathbf{L} \end{array}$	15.0 15.1 15.4 18.8	1160ex/s 1160ex/s 2200ex/s 4980ex/s 7160ex/s	78.4 78.3 78.3 77.3

Lambda Layer will have better results after Convolution.

Experiments

#### Other

Layer	Complexity	Memory (GB)	Throughput	top-1
Global self-attention Axial self-attention Local self-attention (7x7)	$\Theta(blhn^2) \\ \Theta(blhn\sqrt{n}) \\ \Theta(blhnm)$	120 4.8 -	OOM 960ex/s 440ex/s	OOM 77.5 77.4
Lambda layer ( $ k $ =8) Lambda layer (shared embeddings) Lambda convolution (7x7)	$egin{array}{l} \Theta(lkn^2) \ \Theta(lkn^2) \ \Theta(lknm) \end{array}$	0.96 0.48 0.31	1160ex/s <b>1640</b> ex/s 1210ex/s 1100ex/s	<b>78.4</b> 77.9 78.0 78.1

Lambda has higher speed, accuracy and lower memory consumption than Self Attention.

## Other

Config	Params (M)	Throughput	top-1
ResNet101 - 22	24x224		
Baseline	44.6	4600 ex/s	81.3
+ SE	63.6	4000  ex/s	81.8
+ 3 lambda	36.9	4040  ex/s	82.3
+ all lambdas	26.0	2560 ex/s	82.6
ResNet152 - 2:	56x256		
Baseline	60.2	2780 ex/s	82.5
+ SE	86.6	2400 ex/s	83.0
+ 6 lambdas	51.4	2400 ex/s	83.4
+ all lambdas	35.1	1480 ex/s	83.4

Experiments

## Receptive Field

**Other** 

Scope size $ m $	3x3	7x7	15x15	23x23	31x31	global
FLOPS (B)	5.7	6.1	7.8	10.0	12.4	19.4
Top-1 Accuracy	77.6	78.2	78.5	78.3	78.5	78.4

In the experiment, the receptive field of Position Lambda is not the bigger the better.

#### Conclusion

- Lambda Layer can be understood as a better Channel
   + Spatial Attention.
- Compared with Linear Attention, Lambda Layer has the ability to focus better position.
- Lighter and faster than Self Attention.