LambdaNetworks: Modeling long-range Interactions without Attention

Anonymous authors
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- Introduction
- Methodology
- Experiments
- Conclusion

Introduction

利用 Self Attention 獲得上下文資訊對提升模型正確率確實是有幫助的。

但要消耗的記憶體量使其難以應用於超長序列及多維度(如圖像)任務上。

因此，作者提出 lambda network 這個架構，在能獲取上下文資訊的同時減少了記憶體消耗量並提升了運算速度。

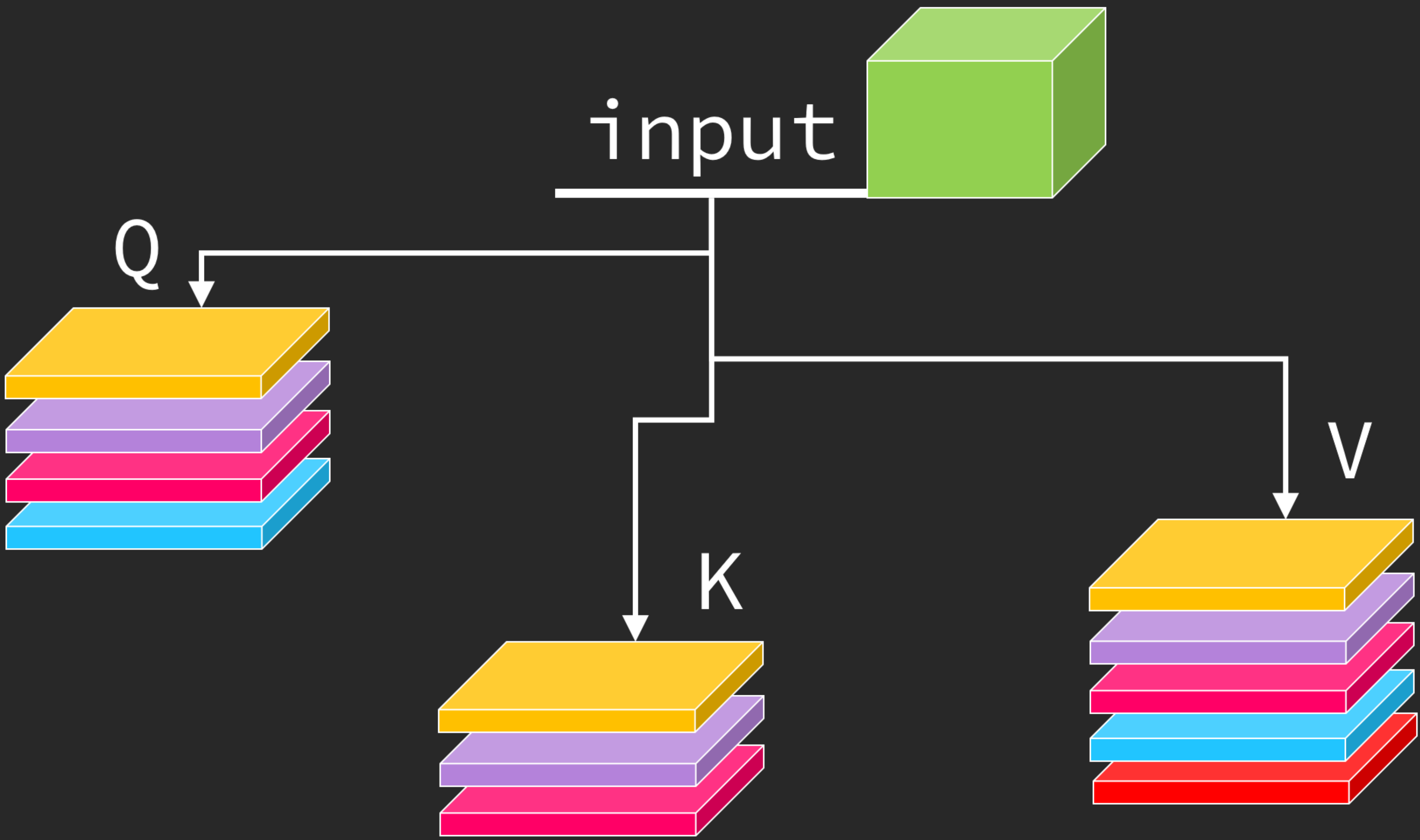
Methodology

Content Lambda

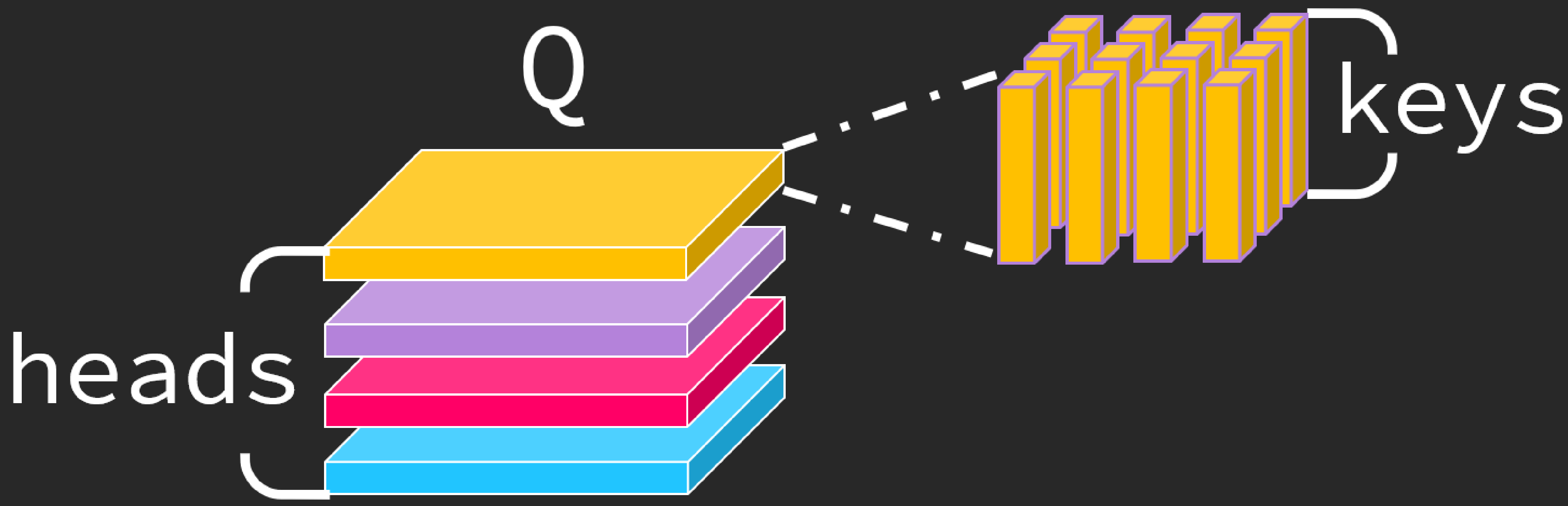
+

Position Lambda

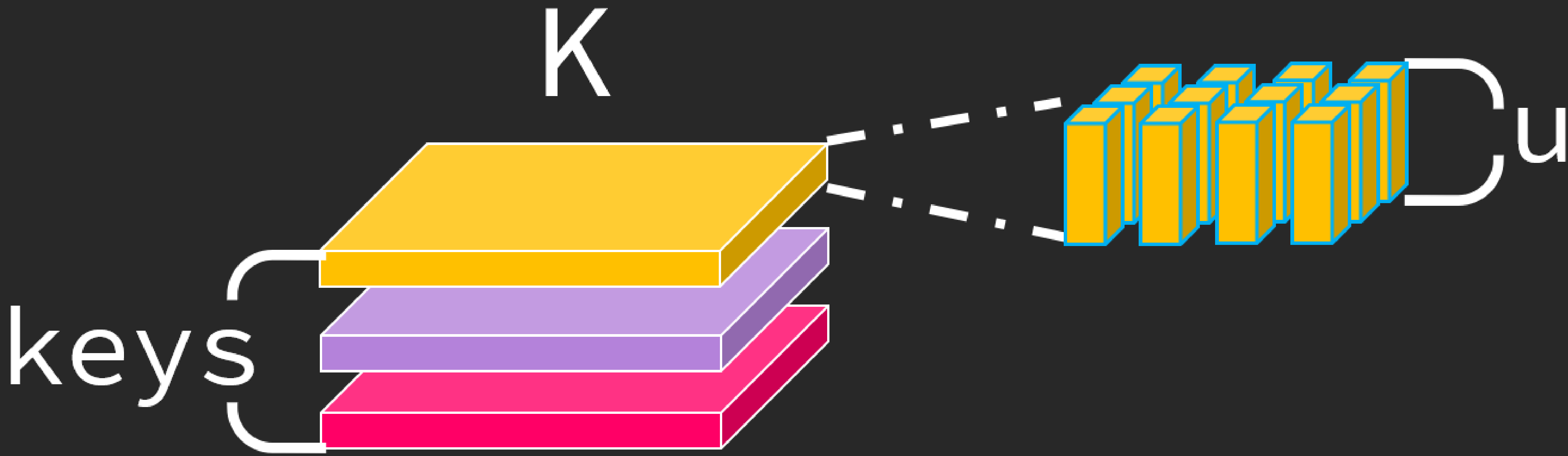
Methodology



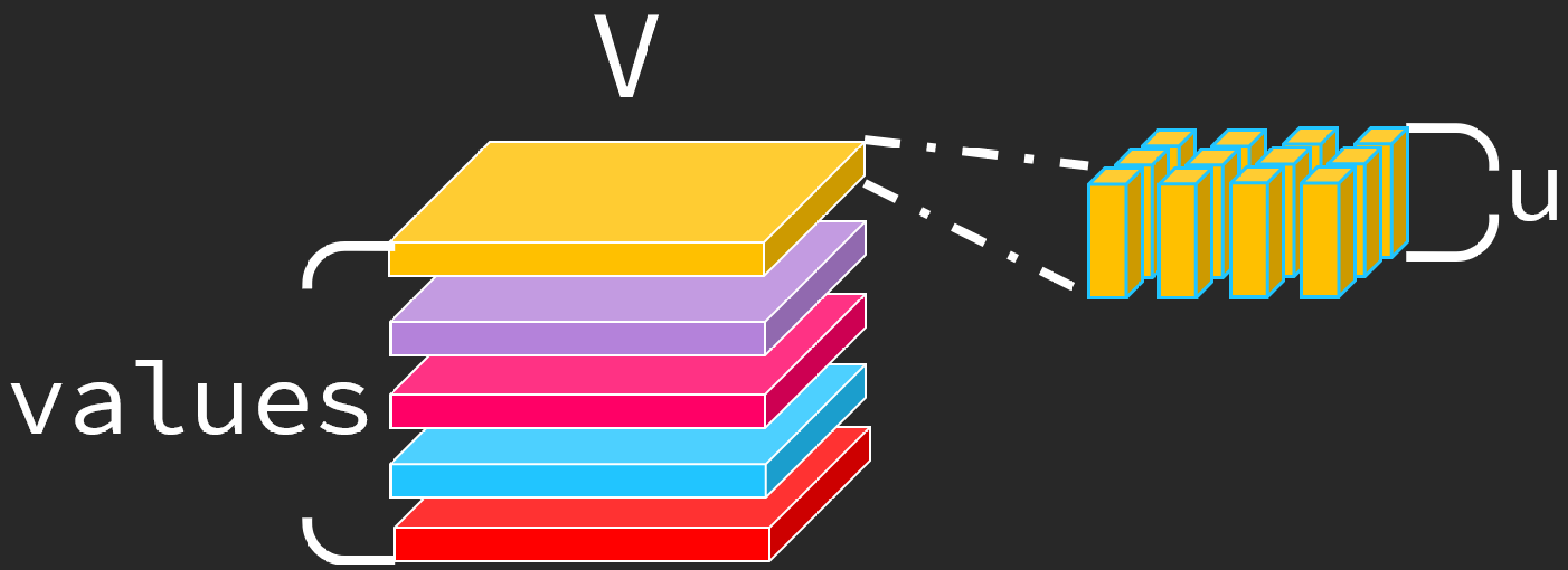
Methodology



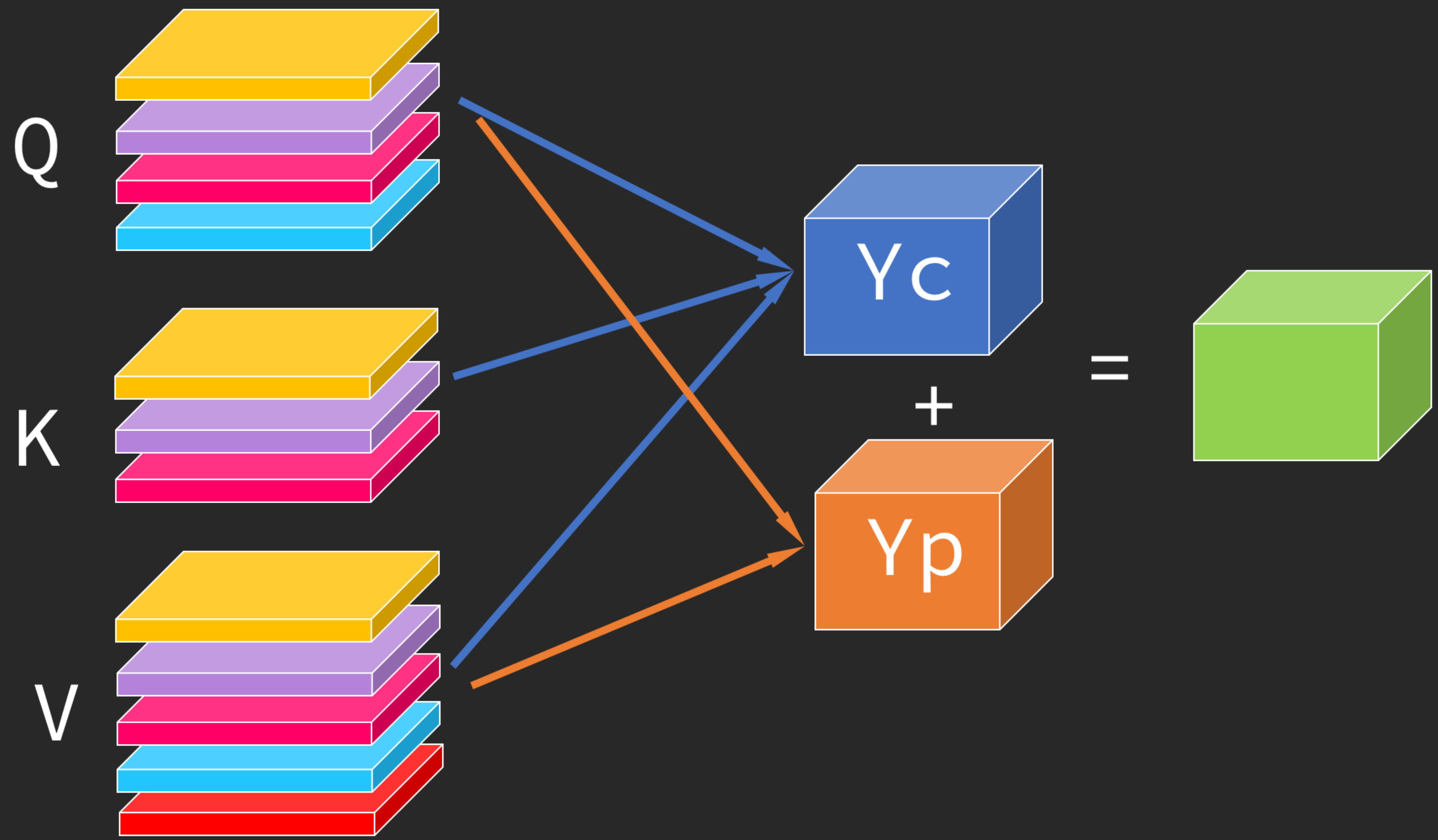
Methodology



Methodology



Methodology

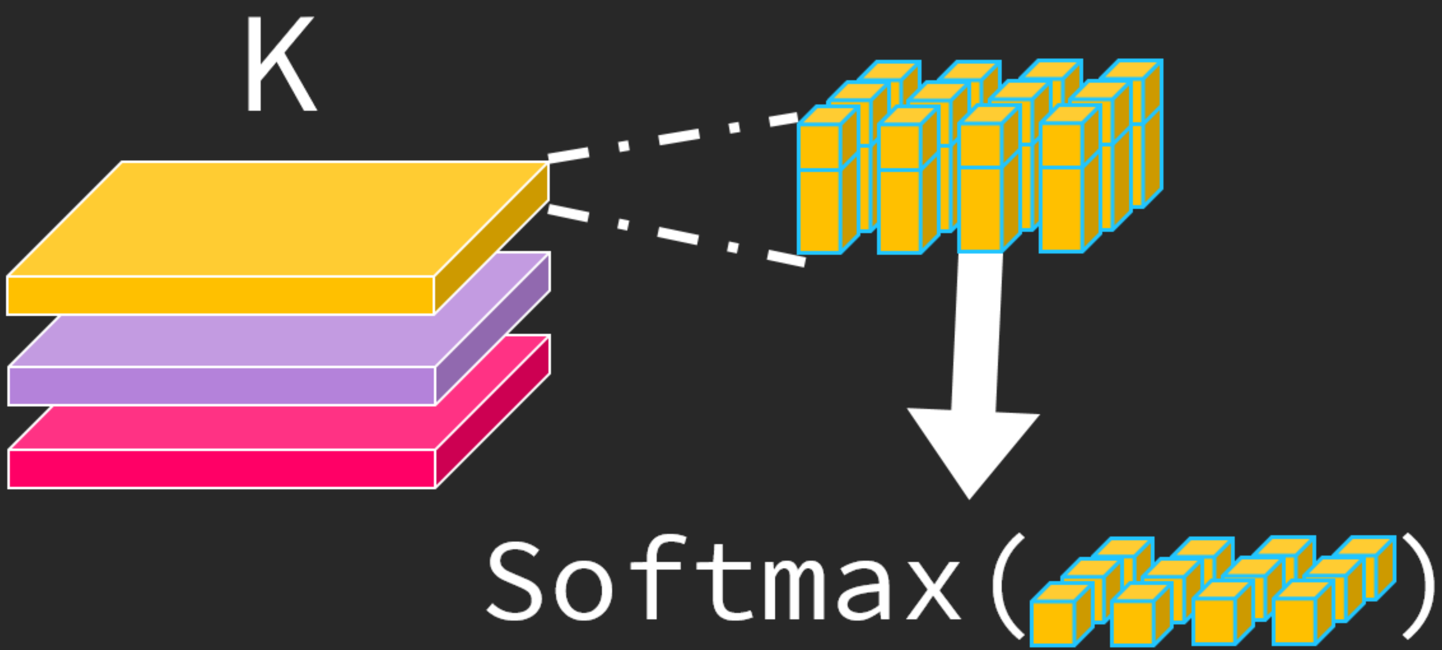


Content Lambda

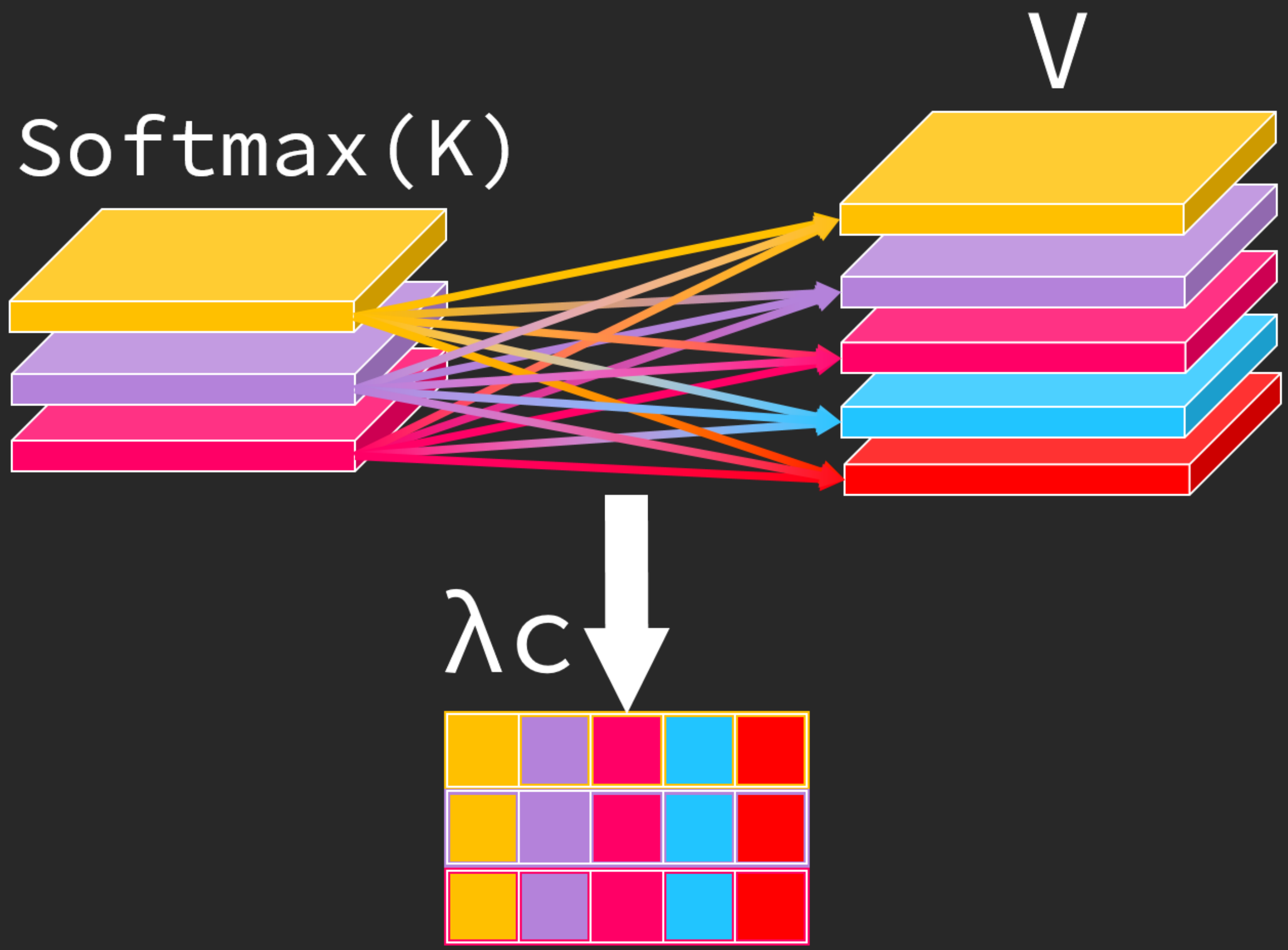
對 Feature「Map」的匹配

Content Lambda

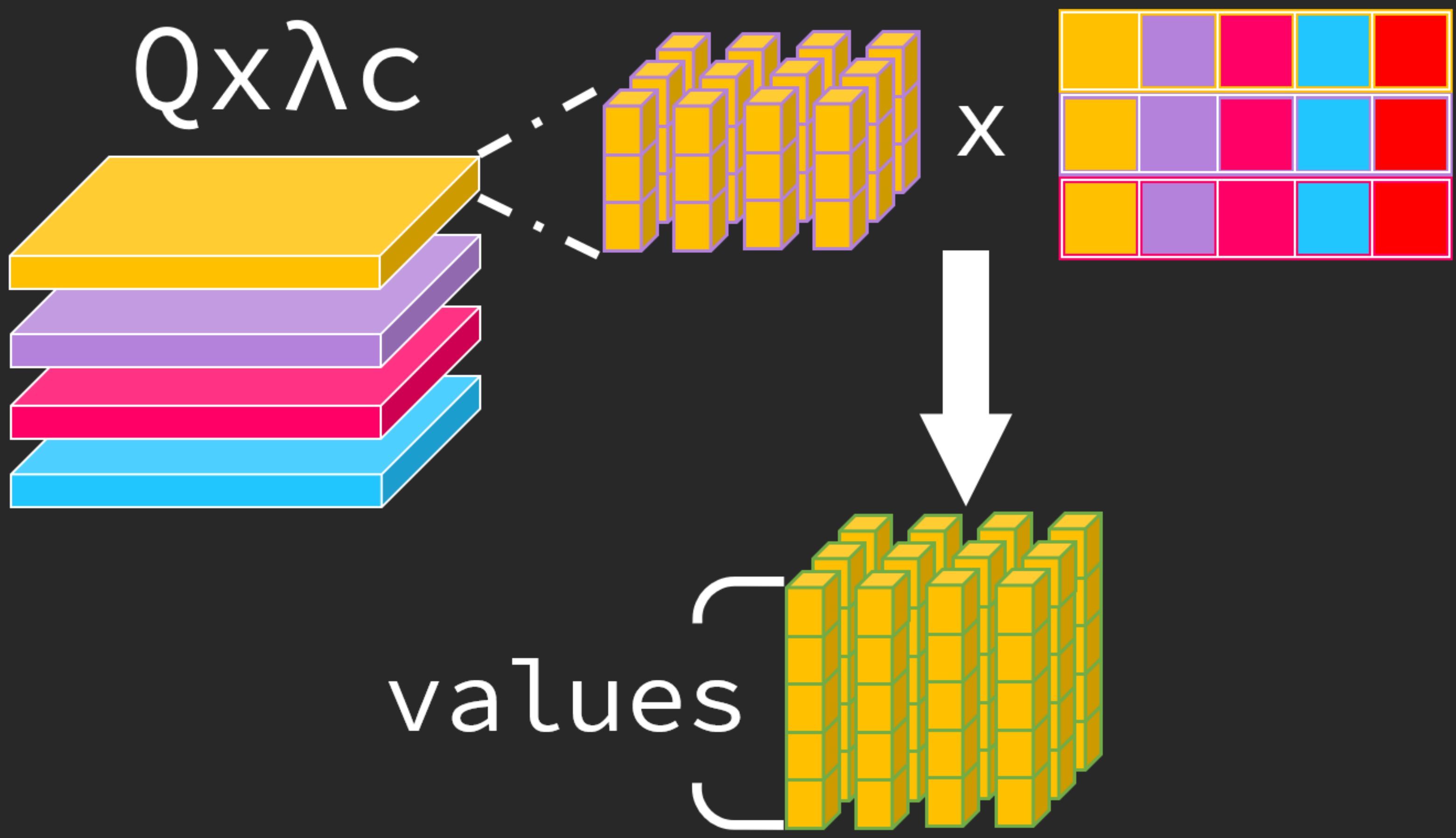
Softmax(K)



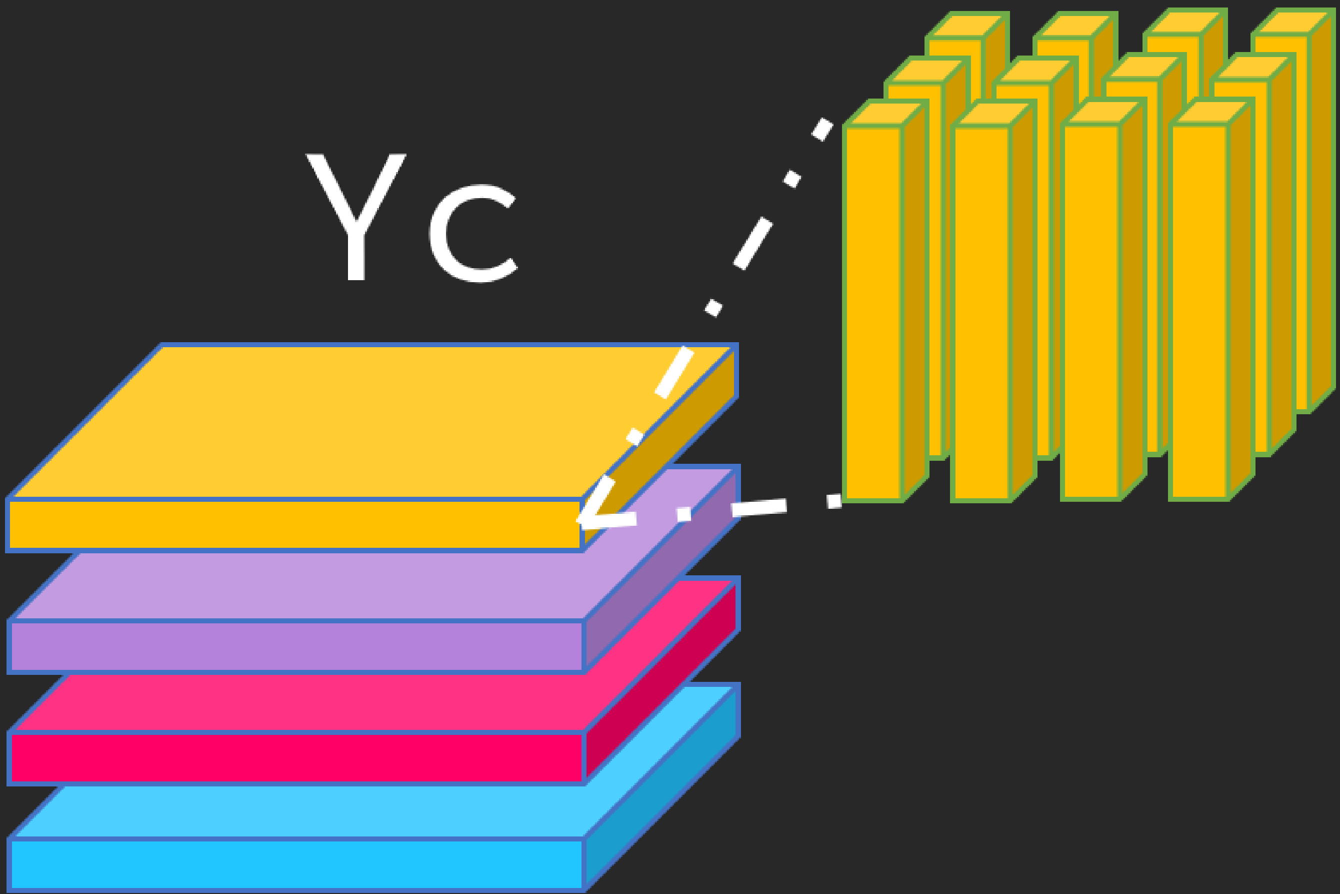
Content Lambda



Content Lambda



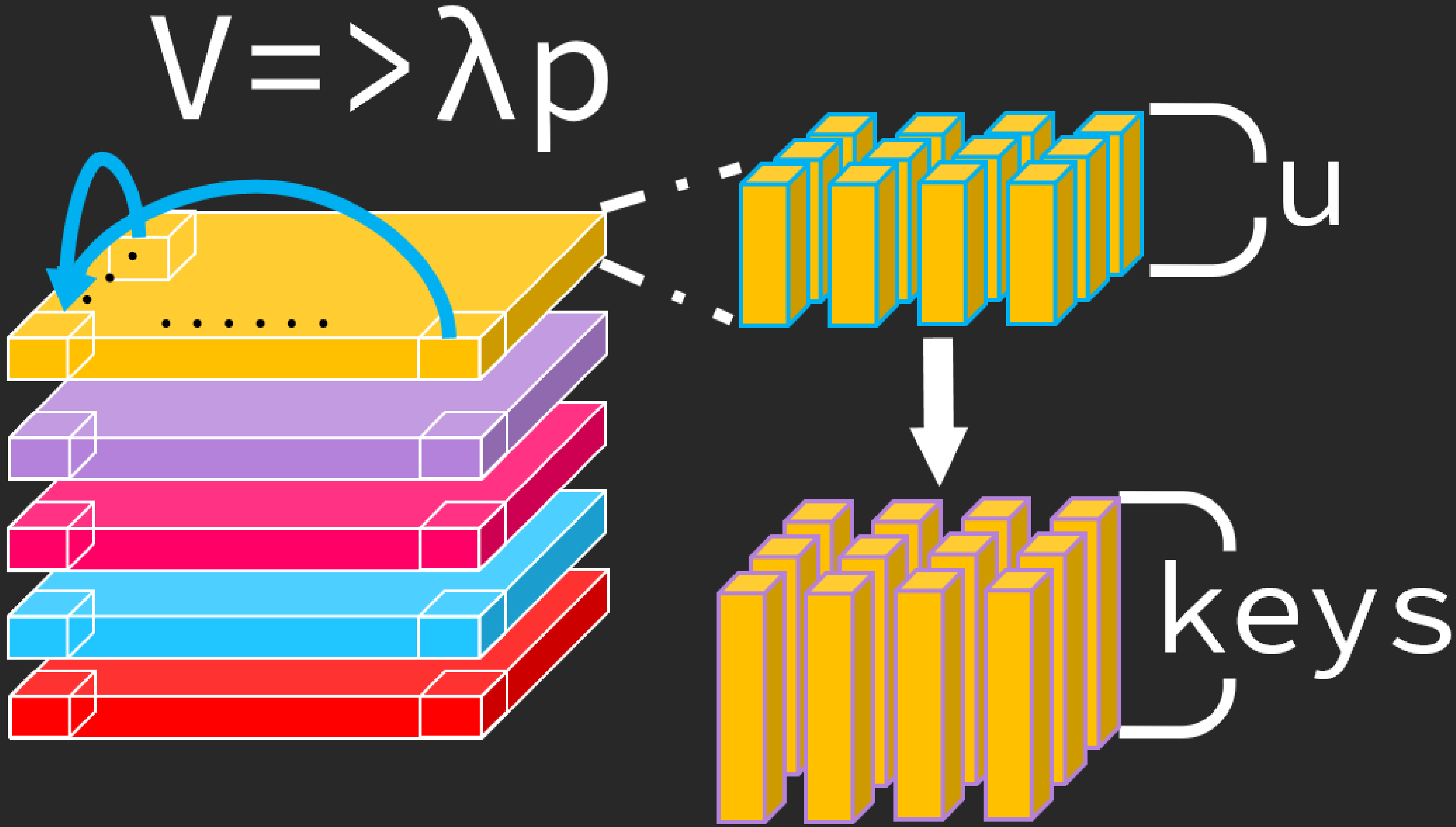
Content Lambda



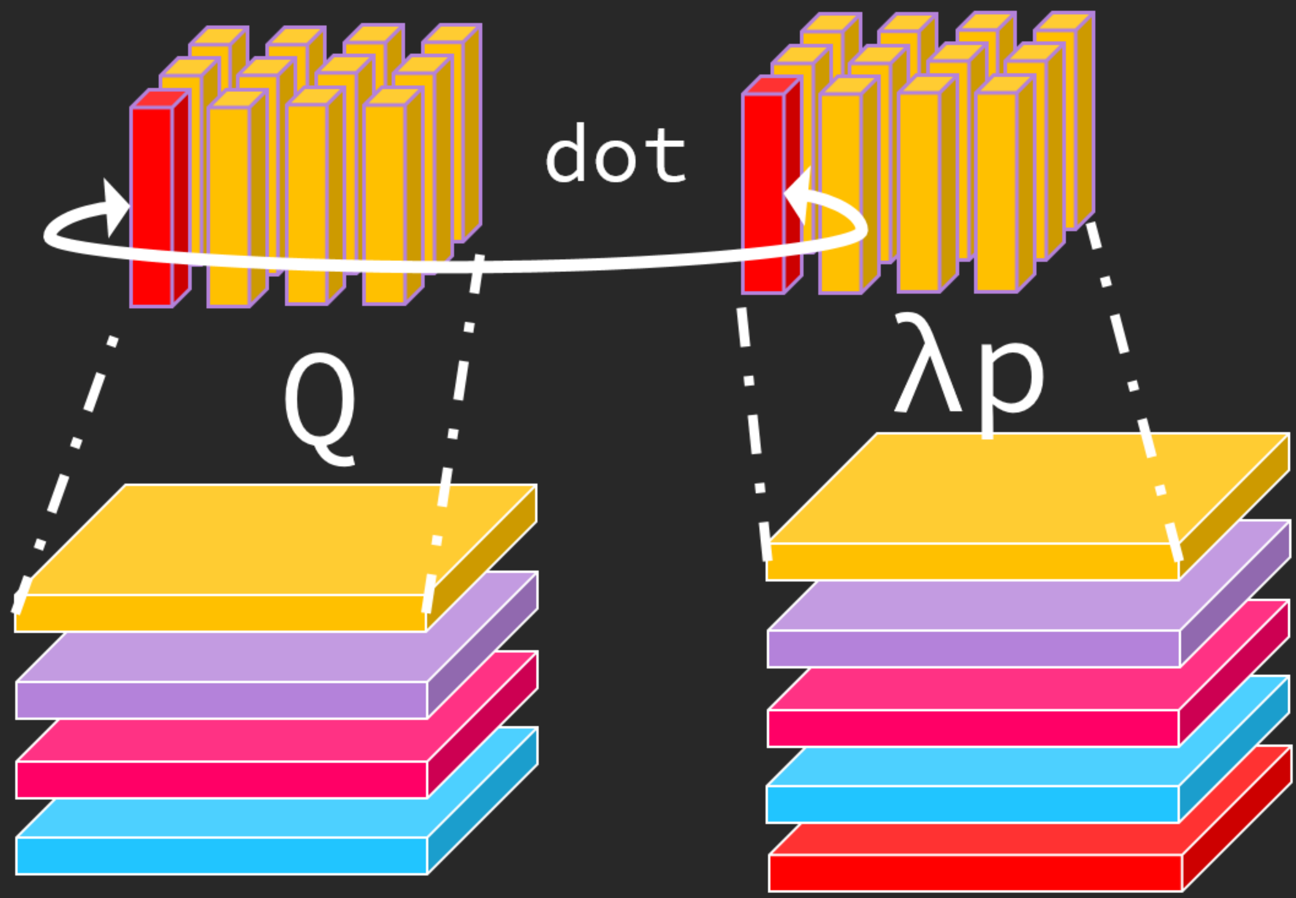
Position Lambda

對 Feature「Vector」的匹配

Position Lambda



Position Lambda



Position Lambda

Experiments

- vs Baseline
- Content vs Position
- Normalization
- Other

Classification

vs Baseline

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

Detection

vs Baseline

Backbone	AP^{bb}_{coco}	$AP^{bb}_{s/m/l}$
ResNet-101	48.2	29.9 / 50.9 / 64.9
ResNet-101 + SE	48.5	29.9 / 51.5 / 65.3
LambdaResNet-101	**49.4**	**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	**50.0**	**31.8 / 53.4 / 67.0**

Segmentation

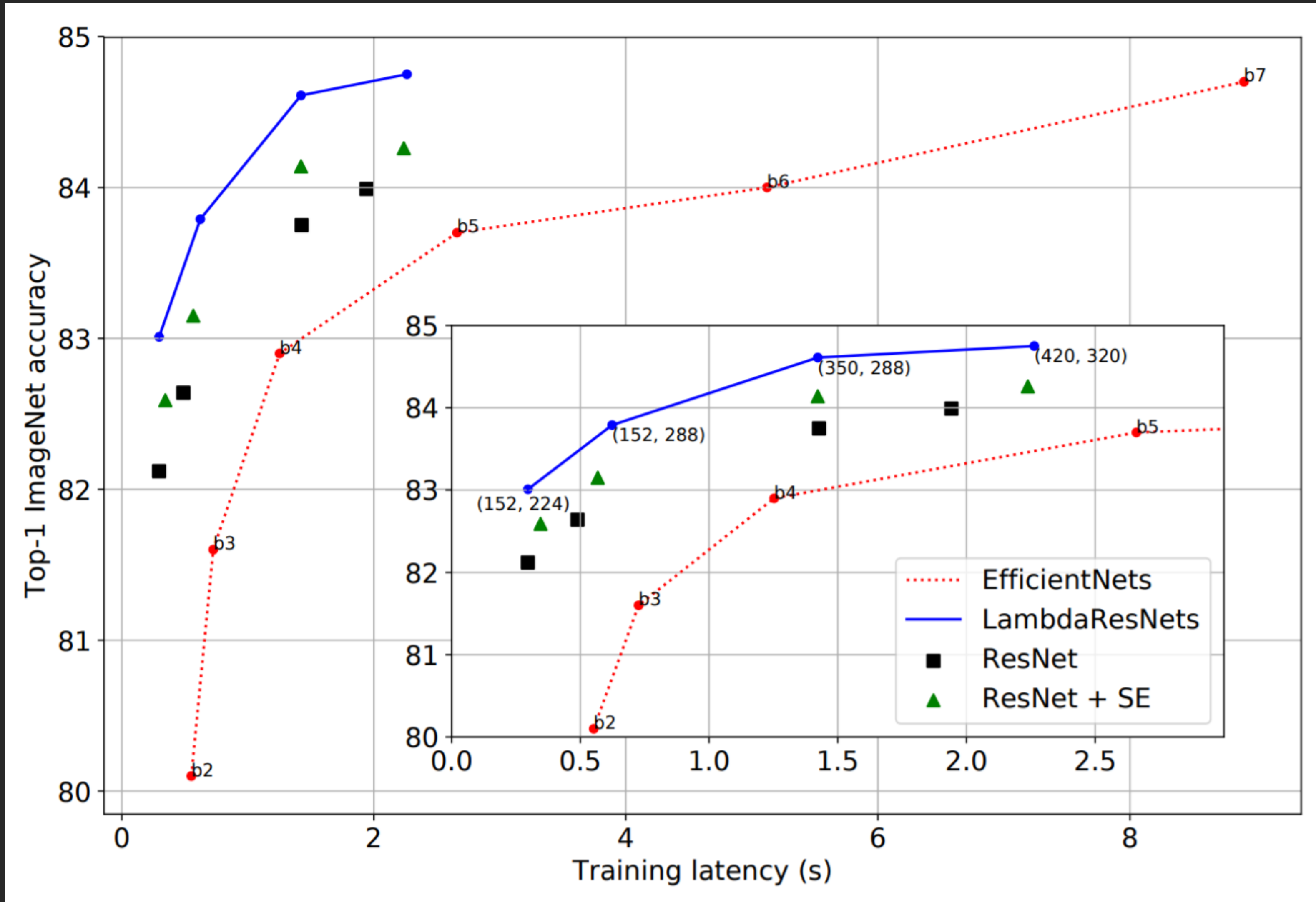
vs Baseline

Backbone	AP_{coco}^{mask}	$AP_{s/m/l}^{mask}$
ResNet-101	42.6	24.2 / 45.6 / 60.0
ResNet-101 + SE	42.8	24.0 / 46.0 / 60.2
LambdaResNet-101	**43.5**	**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	**43.9**	**25.5 / 47.3 / 62.0**

Experiments

Training

vs Baseline



Content vs Position

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

Position Lambda 提供的資訊比起 Content Lambda 更為重要

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

對 K 進行規範是有必要的

Other

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

Lambda Layer 放至於 Convolution 之後會有比較好的效果

Other

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

Lambda 具有比 Self Attention 更高的速度、正確率與更低的記憶體消耗量。

Other

Config	Params (M)	Throughput	top-1
ResNet101 - 224x224			
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 - 256x256			
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

Receptive Field

Scope size $\lvert m \rvert$	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

在實驗中，Position Lambda 的感受野並非是越大越好。

Conclusion

- 可以將 Lambda Layer 理解成為更加優秀的 Channel + Spatial Attention。
- 與 Linear Attention 相比，Lambda Layer 具有更好的位置關注能力。
- 比 Self Attention 更輕便快速。