TDAM: Top-Down Attention Module for Contextually Guided Feature Selection in CNNs

Shantanu Jaiswal, Basura Fernando, Cheston Tan

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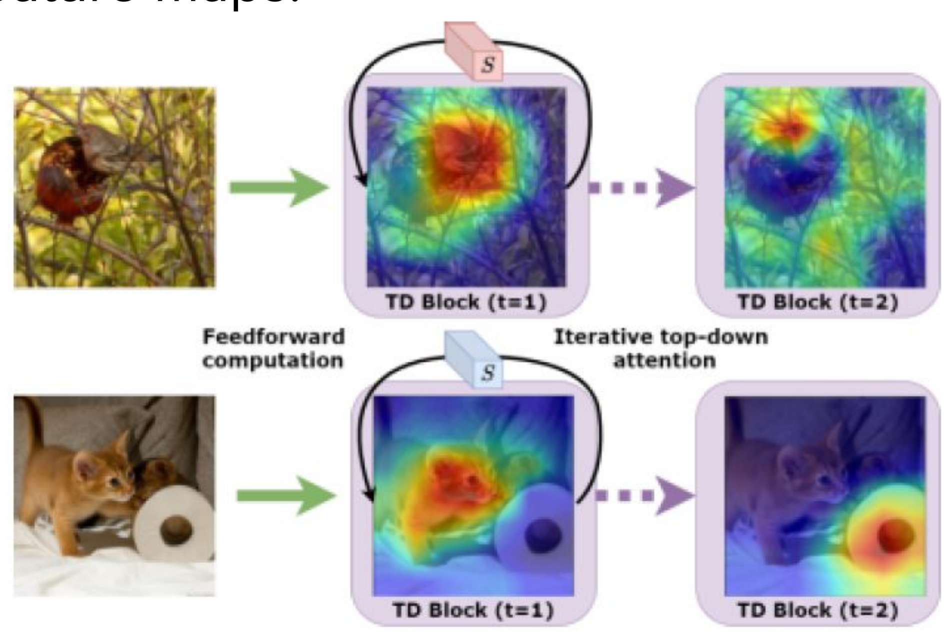
Motivation

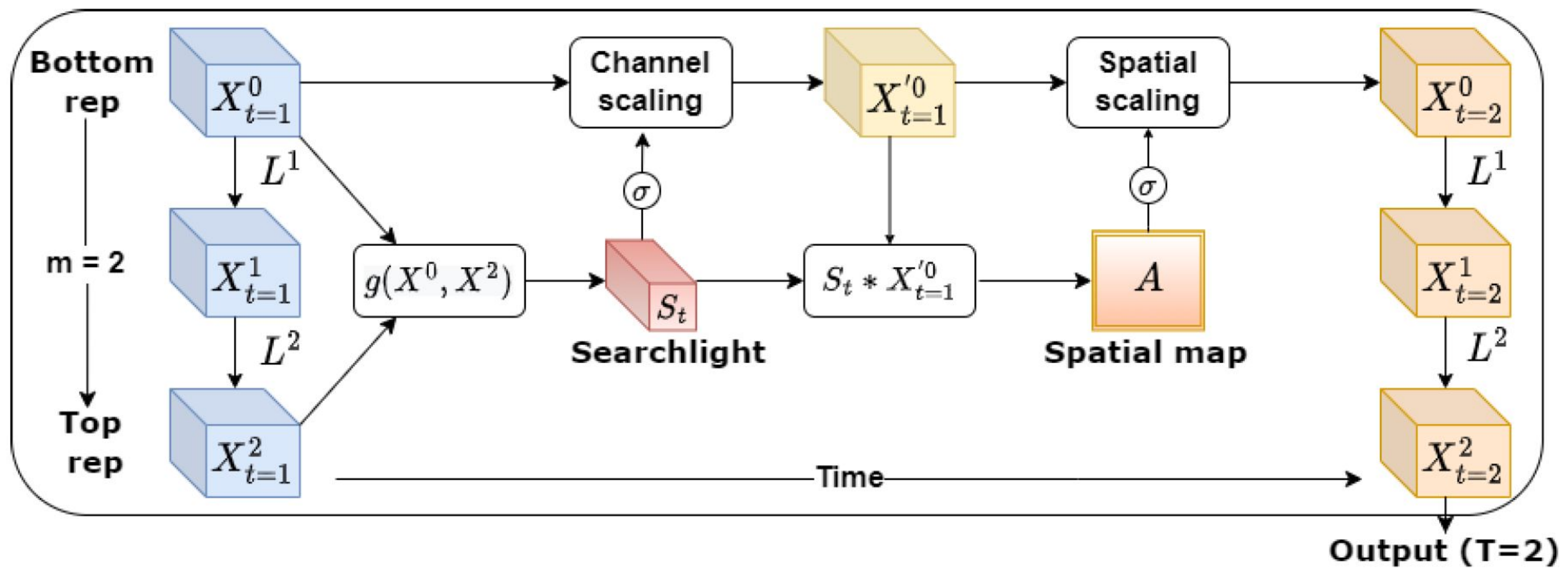
Prominent attention mechanisms for CNNs primarily operate in a feedforward bottom-up manner, thereby being constrained to local information of input feature maps.

Top-down information flow can enable higher-layers to provide semantically-richer contextual information and specify "what and where to look" in lower-level feature maps.



Aim: A lightweight top-down attention module that iteratively generates a "visual searchlight" to perform channel and spatial modulation of its inputs and outputs more contextually-relevant feature maps at each computation step.

Module design



$$X_t^N = L_N(L_{N-1}..(L_1(X_t^0)))$$

$$\mathcal{S}_t = \begin{cases} g(X_t^N, X_t^0) = W_s(\mathrm{ReLU}[W_t(X_{t,p}^N); W_b(X_{t,p}^0)] & \text{if joint attention} \\ g(X_t^N) = W_s[\mathrm{ReLU}(W_t\ (X_{t,p}^N)]) & \text{if top attention} \end{cases}$$

$$X_{t+1}^0 = \boxed{\mathrm{att}(X_t^0; \mathcal{S}_t)}$$

$$X_t'^0 = X_t^0 \otimes \sigma(\mathcal{S}_t)$$

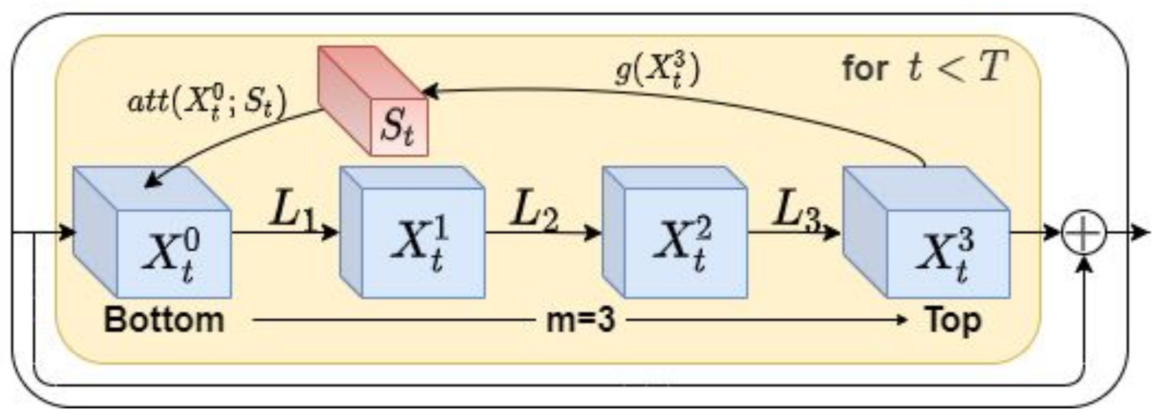
$$\mathcal{A} = \mathcal{S}_t * X_t'^0$$

$$X_{t+1}^0 = X_t'^0 \otimes \sigma(\mathcal{A})$$

Primary module specifications:

1. Number of computation steps ('T')
2. Feedback distance ('m')
3. Attention technique ('joint' or 'top')

Example integration in a ResNet BottleNeck block

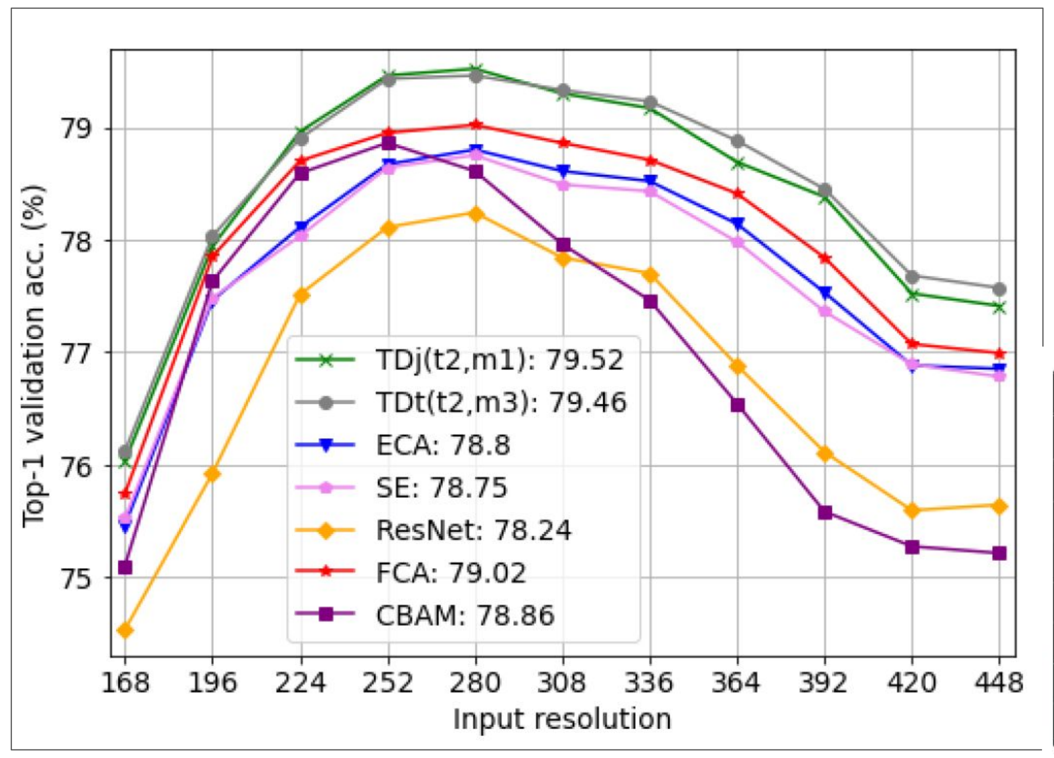


Experiments on ImageNet-1k and resolution robustness

Increases top-1 classification accuracy of a ResNet50 to 79.0% and 67.7% on Ver. 1 and Ver. 2 validation splits respectively.

Outperforms prior state-of-the-art attention modules while having lesser parameters and comparable FPS in most cases (with the exception of ECA).

Method	BB.	Param.	FLOPs	FPS	V2	V1
-	-	-	-	-	Top1	Top1
ResNet (CVPR16)	Resnet50	25.56 M	4.12 G	2143	66.39	77.51
SE (CVPR18)		28.07 M	4.13 G	1911	66.92	78.03
CBAM (ECCV18)		28.07 M	4.14 G	1442	67.28	78.59
ECA (CVPR20)		25.56 M	4.13 G	1989	66.72	78.11
FCA-TS (ICCV21)		28.07 M	4.13 G	1876	67.19	78.70
TDjoint (t=2, m=1)		27.65 M	4.59 G	1890	67.66	**78.96**
TDtop (t=2, m=1)		27.06 M	4.59 G	1905	67.21	78.82
TDtop (t=2, m=3)		27.66 M	5.98 G	1539	**67.70**	78.90
ResNet	Resnet101	44.55 M	7.85 G	1376	69.64	80.36
SE		49.29 M	7.86 G	1201	69.88	80.84
CBAM		49.29 M	7.88 G	862	70.03	81.20
FCA-TS		49.29 M	7.86 G	1164	70.12	81.15
TDjoint (t=2,m=1)		46.75 M	8.37 G	1237	**70.56**	**81.62**
TDjoint(t=2,m=1,L4)		45.94 M	8.01 G	1258	70.28	81.12

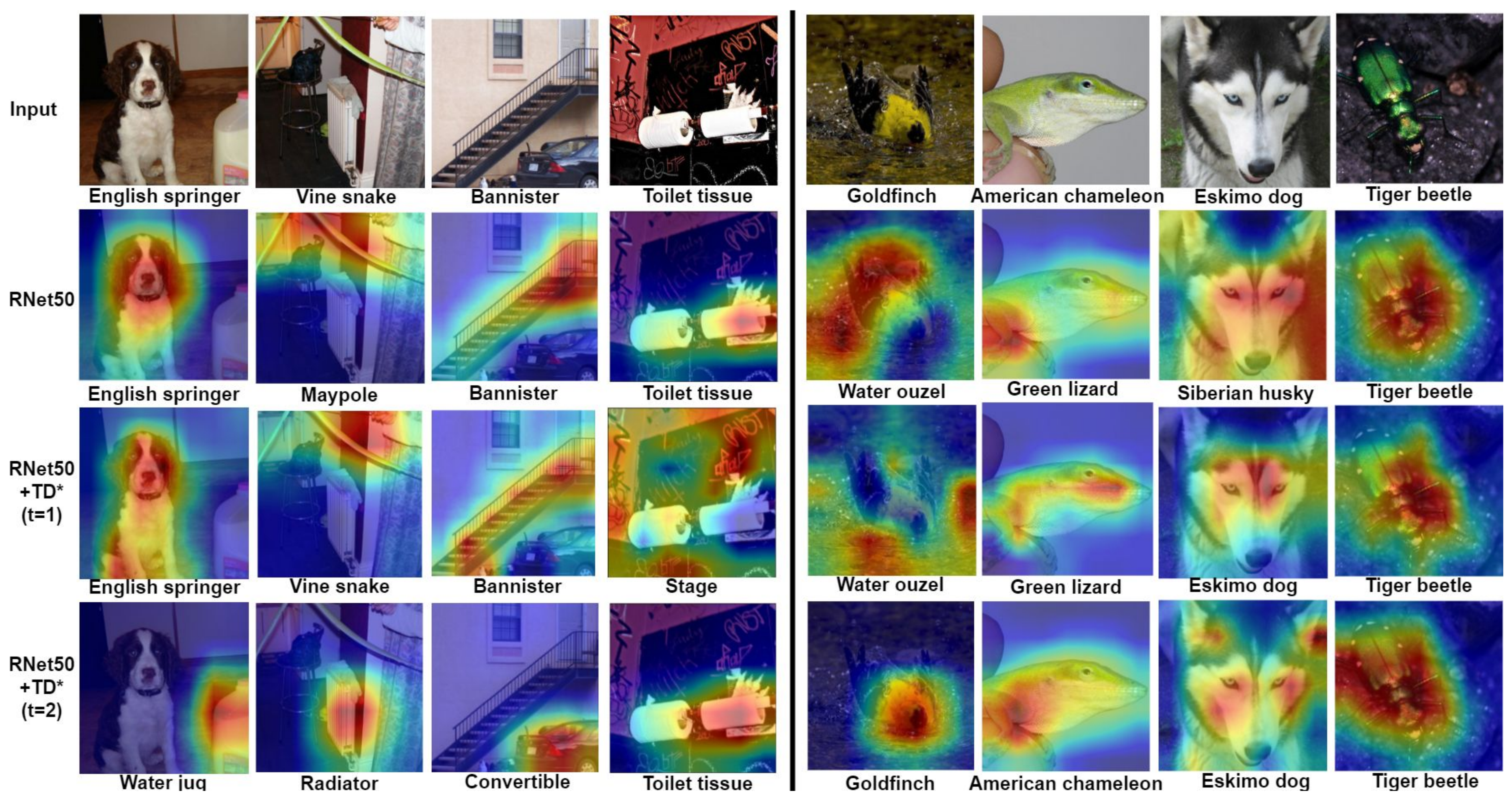


TDAM-models are relatively more robust to changes in input resolution during inference, thereby obtaining better results at higher resolutions.

Model (RNet50)	ImageNet-V1 Top1 Acc.			
-	Best	224^2	168^2	448^2
ResNet	78.24	77.51	74.53	75.64
SE	78.75	78.03	75.52	76.78
CBAM	78.86	78.59	75.10	75.21
ECA	78.80	78.11	75.46	76.85
FCA-TS	79.02	78.70	75.74	76.99
TDjoint(t2,m1)	**79.52**	**78.96**	76.03	77.41
TDtop(t2,m3)	79.46	78.90	**76.12**	**77.57**

Visualizing attention of TDAM-models over time (computation steps)

- TDAM-models learn to "shift attention" by localizing individual objects or features at each computation step without any explicit supervision.
- Visualization script provided in source code to try on arbitrary examples.



(Localizing individual objects) (Localizing relevant features)

Weakly-supervised object localization and other recognition tasks

Model	ImageNet(V1)	
-	Top1	Top5
RNet50	57.04	68.67
RNet101	58.54	69.86
RNet50 + SE	56.62	67.88
RNet50 + CBAM	58.91	70.54
RNet50 + ECA	56.94	68.38
RNet50 + FCA-TS	56.88	67.86
RNet50 + TDjoint(t=2,m=1)	61.55	72.10
RNet50 + TDtop(t=2,m=3)	**61.97**	**72.37**

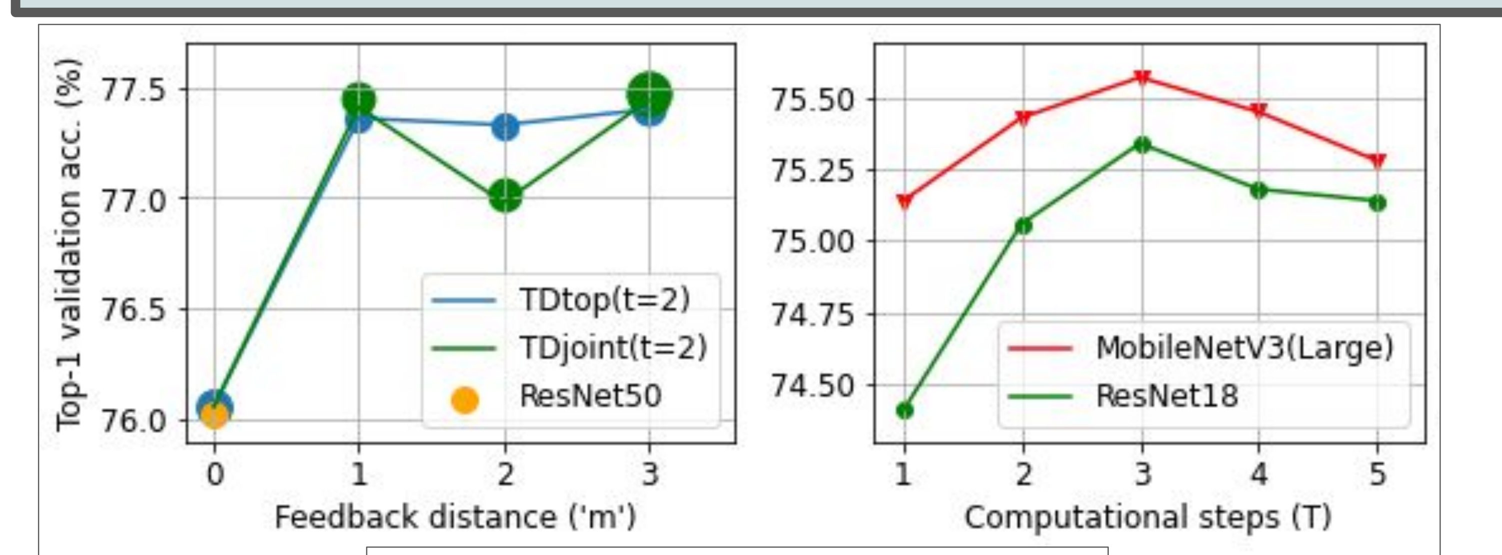
Improves weakly supervised localization acc. by 5% indicating more precise feature activation maps.

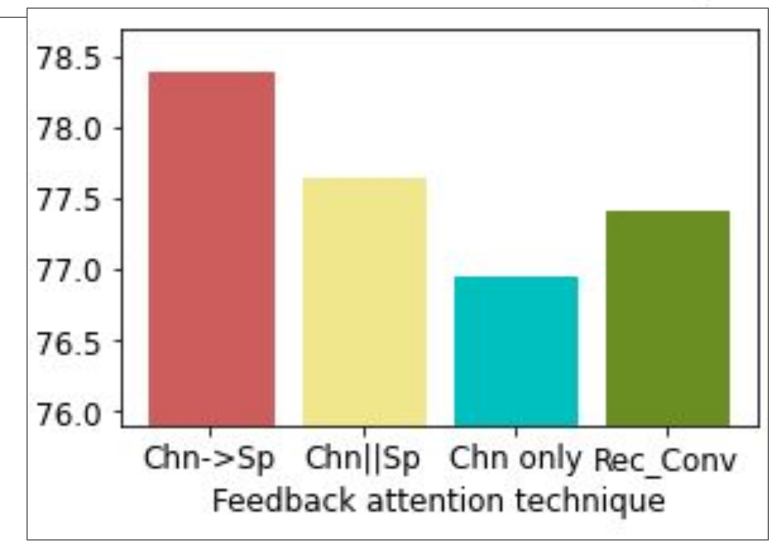
Improves state-of-the-arts for fine-grained (CUB, Stanford Dogs) and multi-label (MS-COCO) object recognition.

Model (ResNet50)	CUB	Dogs	MS-COCO	
-	Top1	Top1	mAP	F1-O
ResNet	88.26	85.97	77.58	75.45
SE	88.89	86.55	78.21	76.37
CBAM	89.37	86.98	79.17	77.15
FCA-TS	88.94	86.76	79.05	77.08
TDjoint(t=2,m=1)	89.61	87.08	**79.61**	**77.71**
TDtop(t=2,m=3)	**89.75**	**87.30**	79.56	77.62

- Improvements on multiple tasks and benchmarks suggest benefits of feedback-driven channel and spatial attention in enabling iterative task-specific refinement of constituent feature maps within the backbone.

Ablation study (Impact of feedback steps, distance and technique)





(Ablations performed on a hierarchically-reduced subset of ImageNet-1k comprising 200 classes; Further analyses in paper)

Source code and models publicly available at: https://github.com/shantanuj/TDAM_Top_down_attention_module