# Implicit Differentiable Outlier Detection Enables Robust Deep Multimodal Analysis 



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## Popular tasks for Multimodal pipelines

## Input <br> Output



Sentence:
One image features multiple ducks on a country road, and the other image shows a mass of white ducks that


Answers:

Common mis-prediction : radio $x$

Ours: electricity

## Output



Common mis-prediction : True
Answers:
 are not in flight. Can We Use exterinall knowledge in MM pipelines?

## Augmenting External knowledge in MM pipeline via KG

Caption:
A man riding a bicycle down a city street.


Another challenge: How to align external knowledge in MM pipeline?

## Implicit OOD detection layer: Out-ofDistribution detection using EM iterations

$$
\begin{array}{ccccc}
F(x ; \Theta) & F(x ; \Theta) & \cdots & F(x ; \Theta) & F(x ; \Theta) \\
t=1 & t=2 & & t=T-1 & t=T
\end{array}
$$



We approximated the density of multimodal features for outlier detection.

## Implicit Differentiable OOD detection layer

$$
\begin{gathered}
F(x ; \Theta) \\
t=T-1
\end{gathered}
$$

EM-based algorithm as a fix point iteration:

$$
\begin{equation*}
\mu_{k}^{t+1} \leftarrow \frac{\sum_{i=1}^{N} \exp \left(-w\left(\mu_{k}^{t}\right)\right) x_{i}}{\sum_{i=1}^{N} \exp \left(-w\left(\mu_{k}^{t}\right)\right)} \tag{1}
\end{equation*}
$$

GEM score for Outlier Detection:

$$
\begin{equation*}
s\left(l_{j}\right)=\log \sum_{k=1}^{K} \exp \left(-\frac{1}{2}\left(l_{j}-\mu_{k}^{*}\right)^{T} \sigma_{k}^{-1}\left(l_{j}-\mu_{k}^{*}\right)\right) \tag{2}
\end{equation*}
$$

Jacobian-Free backprop [1] $\qquad$
[1] Fung, Samy Wu, et al. "Jfb: Jacobian-free backpropagation for implicit networks." Proceedings of the AAAI Conference on Artificial Intelligence. Vol. 36. No. 6. 2022.

## Efficient Backpropagation for OOD Detection Layer



- We use Jacobian-Free Backpropagation (JFB) to unroll the last few iterates of the EM algorithm for gradient.


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## Our final VK-OOD Multimodal pipeline



## Experiments - Backpropgation methods

- We used different backpropgation methods in OOD detection layer with ViLT as the backbone.
- JFB-EM gained 76.8\% in term of accuracy on VQAv2 task with $1 / 4$ backward time comparing to vanilla EM.

| Method | \#Param(M) | \#FLOPs(G) | Time(m)/epoch | Max Mem(Mb) | VQAv2 |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 185.2 | 39.6 |  | 18673 | 76.6 |
| JB-EM | 125.2 | 115.7 | 39.6 | 12.7 | 14512 | 76.6 |
| JFB-EM | 124.8 | 108.6 | 39.6 | 6.3 | 13674 | 76.8 |

Table 1: Experimental results of different backpropagation method in the dense OOD detection layer. JFB-EM is much more efficient in backward pass and use less memory. It also outperforms on the VQAv2 task in terms of accuracy.

## Experiments - Downstream tasks

| Model | \#Params | VQAv2 | NLVR2 | COCO |  | Flickr30k |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  | TR R@5 | IR R@5 | TR R@5 | IR R@5 |
| ViLT | 87 | 70.3 | 74.6 | 86.2 | 72 | 95.6 | 86.8 |
| UNITER | 155 | 72.7 | 75.8 | 87.4 | 78.5 | 97.1 | 92.4 |
| ALBEF | 314 | 74.5 | 80.5 | 91.4 | 81.5 | 99.4 | 96.7 |
| VinVL | 157 | 75.9 | 83.1 | 92.6 | 83.2 | - | - |
| BLIP* | 346 | 77.5 | 82.8 | 95.2 | $\mathbf{8 5 . 4}$ | $\mathbf{9 9 . 8}$ | $\mathbf{9 7 . 5}$ |
| VK-OOD-s(ViLT) | 87.4 | 76.7 | 84.3 | 90.9 | 81.6 | 97 | 94.3 |
| VK-OOD-s(CLIP) | 113.4 | 76.2 | 83.8 | 92.8 | 83.4 | 99.6 | 96.7 |
| VK-OOD-s(BLIP) | 346.4 | 77.8 | 84.1 | $\mathbf{9 5 . 4}$ | $\underline{85.2}$ | $\mathbf{9 9 . 8}$ | 97.2 |
| VK-OOD-1(ViLT) | 125 | 76.8 | $\mathbf{8 4 . 6}$ | 91.7 | 81.3 | 97.2 | 94.5 |
| VK-OOD-l(CLIP) | 151 | 76.1 | 83.9 | 93.1 | 83.6 | 99.6 | 96.8 |
| VK-OOD-1(BLIP) | 412 | $\mathbf{7 7 . 9}$ | $\underline{84.5}$ | 95.1 | 84.8 | 99.6 | 97.1 |

Table 5: Overall performance on multiple downstream tasks. We demonstrate VK-OOD scale with different model backbones and achieve the best and second-best results. VK-OOD-s is the scalar case, and VK-OOD-1 is the dense case. *our implementation.

## Experiments - Qualitative Analysis




Original


A man riding bicycle


Car locates on street


Bus locates on street


Traffic lights locate on street


Buildings locate on street

## Contributions

Caption: A man riding a bicycle down a city street. Question: Is this person crossing illegally or legally?


O ConceptNet


## Contributions

- We mainly aim to integrating implicit and explicit knowledge seamlessly in vision-language model.
- It is crucial to identify high-quality knowledge during forward pass due to error propagation that may affect downstream predictions.
- We propose an end-to-end framework with the implicit differentiable outlier detection layer to filter noise knowledge during training.

Thanks for your attention! Q\&A

$\stackrel{F}{=}$ Paper


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