

Learning Discriminative Representations to Interpret Image Recognition Models

Thèse de Doctorat

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Table of Contents

- Introduction
- 1** Background
- 2** Opti-CAM: Optimizing saliency maps for interpretability
- 3** CA-Stream: Attention-based pooling for interpretable image recognition
- 4** A learning paradigm for interpretable gradients
- References

Table of Contents

■ Introduction

1 Background

2 Opti-CAM: Optimizing saliency maps for interpretability

3 CA-Stream: Attention-based pooling for interpretable image recognition

4 A learning paradigm for interpretable gradients

■ References

Motivation: Low stakes

My go to exercise is running, **but...**

Motivation: Low stakes

My go to exercise is running, **but...**

I think my running shoes
are getting *worn*



Motivation: Low stakes

My go to exercise is running, **but...**

I think my running shoes
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I want a replacement,
but I know about
machines, not shoes!



still, I know my phone can
identify my current shoes

Motivation: Low stakes

My go to exercise is running, **but...**

I think my running shoes
are getting *worn*



I want a replacement,
but I know about
machines, not shoes!



and obtain a new pair
of the shoes I like



The Nike Free RN Distance 2

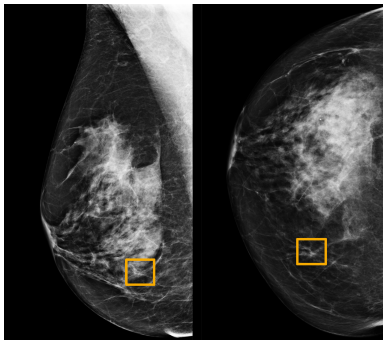
still, I know my phone can
identify my current shoes

Motivation: Raising the stakes

Now let's consider riskier situations:

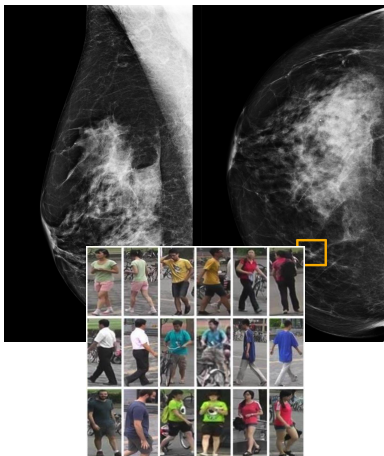
Motivation: Raising the stakes

Now let's consider riskier situations:



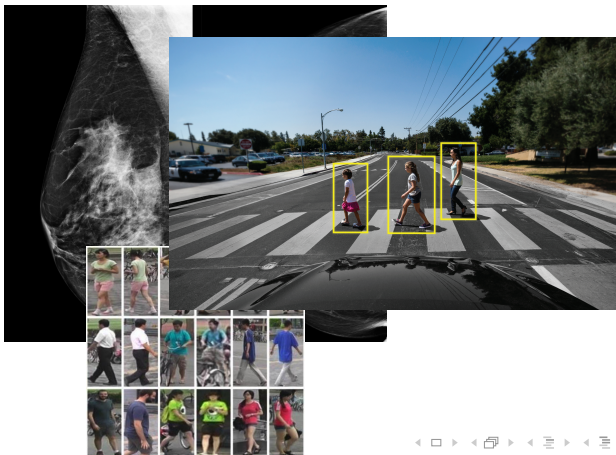
Motivation: Raising the stakes

Now let's consider riskier situations:

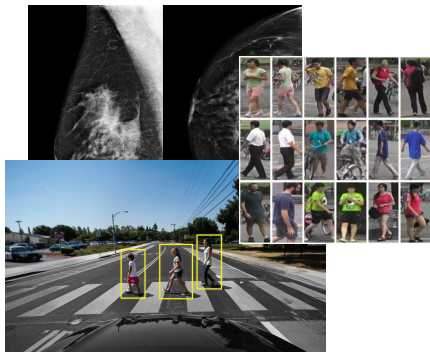


Motivation: Raising the stakes

Now let's consider riskier situations:



Motivation: Straight to the point



- How do we know **how** safe a system is?

Motivation: Straight to the point



- How do we know **how** safe a system is?
- How do we **know** how a system works?

Motivation: Straight to the point



- How do we know **how** safe a system is?
- How do we **know** how a system works?
- If a system fails, **who** is accountable?

Let's slow for a bit
and go step by step:

Computation, Computer Vision and AI

[1]

Table of Contents

- Introduction
- 1** Background
- 2 Opti-CAM: Optimizing saliency maps for interpretability
- 3 CA-Stream: Attention-based pooling for interpretable image recognition
- 4 A learning paradigm for interpretable gradients
- References

This is a text in second frame. For the sake of showing an example.

- Text visible on slide 1

Table of Contents

- Introduction
- 1 ■ Background
- 2 ■ Opti-CAM: Optimizing saliency maps for interpretability**
- 3 ■ CA-Stream: Attention-based pooling for interpretable image recognition
- 4 ■ A learning paradigm for interpretable gradients
- References

Table of Contents

- Introduction
- 1 ■ Background
- 2 ■ Opti-CAM: Optimizing saliency maps for interpretability
- 3 ■ CA-Stream: Attention-based pooling for interpretable image recognition**
- 4 ■ A learning paradigm for interpretable gradients
- References

Table of Contents

- Introduction
- 1 ■ Background
- 2 ■ Opti-CAM: Optimizing saliency maps for interpretability
- 3 ■ CA-Stream: Attention-based pooling for interpretable image recognition
- 4 ■ A learning paradigm for interpretable gradients**
- References

Table of Contents

- Introduction
- 1 Background
- 2 Opti-CAM: Optimizing saliency maps for interpretability
- 3 CA-Stream: Attention-based pooling for interpretable image recognition
- 4 A learning paradigm for interpretable gradients
- References

References I



Z. C. Lipton, “The mythos of model interpretability: In machine learning, the concept of interpretability is both important and slippery.” *Queue*, vol. 16, no. 3, pp. 31–57, 2018.