Learning Discriminative Representations to Interpret Image Recognition Models

Thèse de Doctorat

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Motivation

Low Stakes

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

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I think my running shoes
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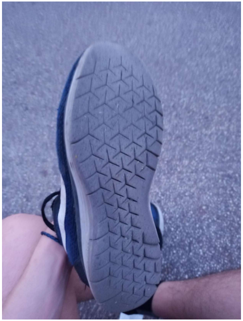

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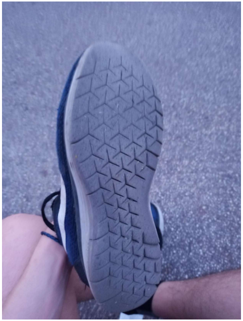

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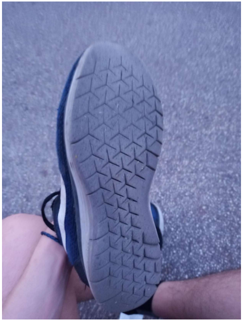

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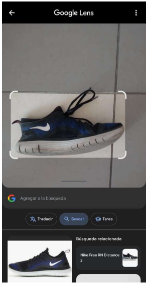

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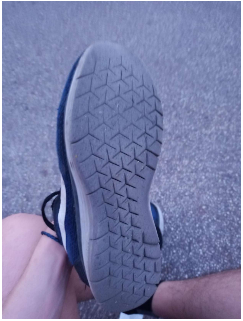

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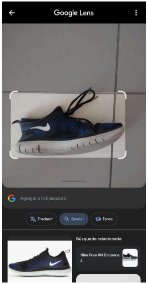

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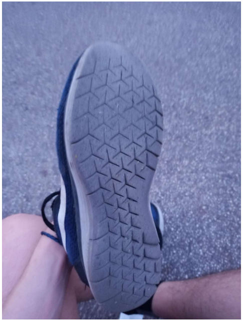

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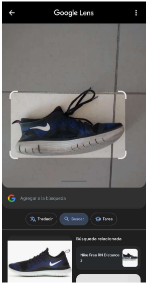

My phone can *identify* my current shoes

Nike Free RN Distance 2

***How* could my phone identify that model?**

Motivation

Raising the stakes

Now let’s consider riskier situations:

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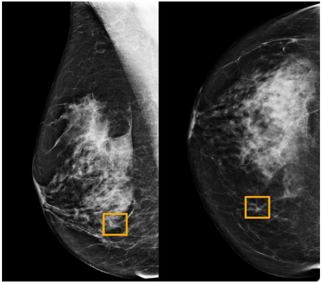

Motivation

Raising the stakes

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Raising the stakes

Now let's consider riskier situations:

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Straight to the point

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

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Straight to the point

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

We must **understand** the behaviour of these models.

Step by step

Computation, Computer Vision and AI → Explainable AI → Thesis objectives

Computation, Computer Vision and AI

Computation

Alan Turing forefather of current computer science.

Better known as *Computer Science*.

Computation, Computer Vision and AI

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Alan Turing forefather of current computer science.

Better known as *Computer Science*.

Study of:

- Algorithms.
- Data structures.
- Design of hardware and software.

Computation, Computer Vision and AI

Computer Vision

Replication of human vision capabilities.

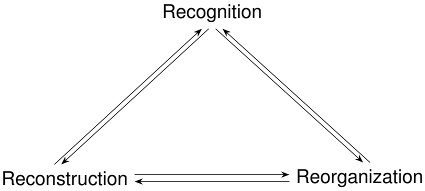
Computation, Computer Vision and AI

Computer Vision

Replication of human vision capabilities.

Three fundamental tasks[1]:

- Recognition.
- Reconstruction.
- Reorganization.



Computation, Computer Vision and AI

Artificial Intelligence

Systems capable of performing tasks requiring human intelligence [2].

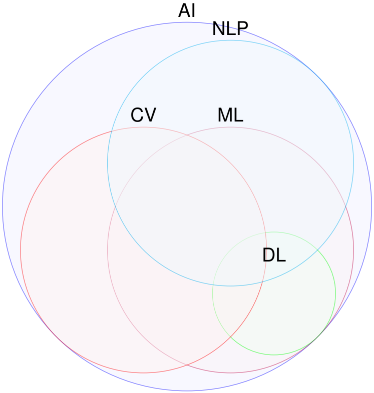
Computation, Computer Vision and AI

Artificial Intelligence

Systems capable of performing tasks requiring human intelligence [2].

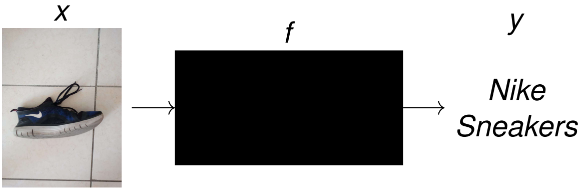
Subfields:

- Machine Learning *(ML)* & Deep Learning (*DL*).
- Computer Vision(*CV*).
- Natural Language Processing (*NLP*).
- Robotics.



Explainable AI

We are interested in understanding models, behaving like a black box model:



x

f

y

Nike Sneakers

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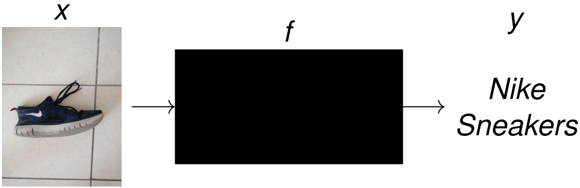
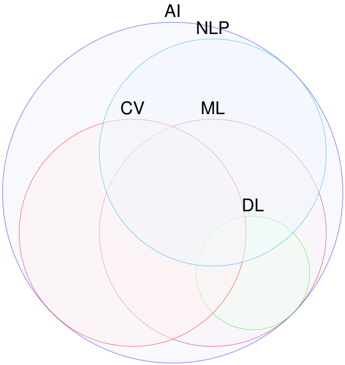


x $\longrightarrow$ f $\longrightarrow$ y

Nike Sneakers

We want to *know why* $f(x) \to y$

Fitting it all together



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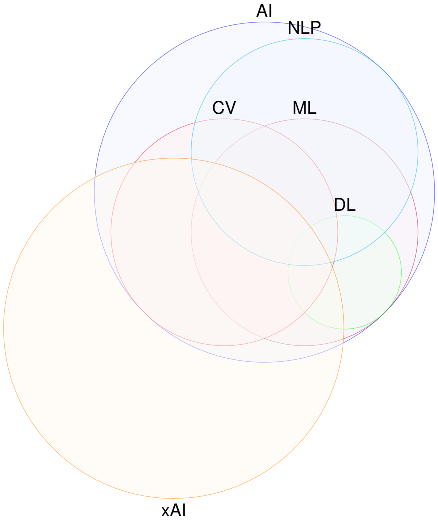

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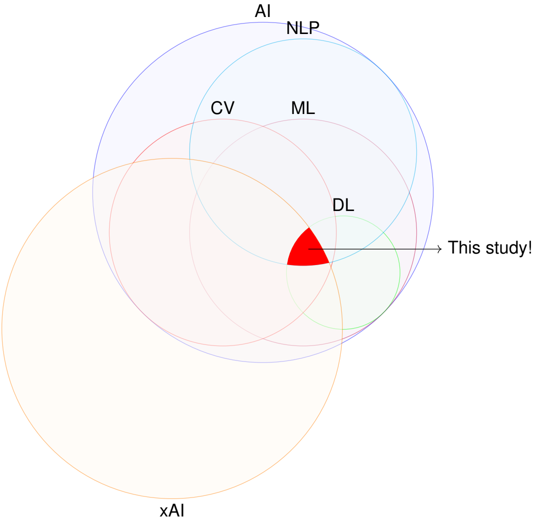

Thesis Objectives

Improvement of recognition and interpratable properties of model predictions.

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In particular:

- Development of low cost/complexity explainability approaches.

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Improvement of recognition and interpratable properties of model predictions.

In particular:

- Development of low cost/complexity explainability approaches.
- Establishment of a fixed evaluation protocol.
- Differenciation of human based and machine explanations.

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Background

To familiarize with this work, we split it into three points:

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Preliminaries

- Approaching Vision.
- David Marr’s approach.
- CV currently.
- Desiredata of Interpretability Study.

Image Recognition Models

- Traditional Models.
- Convolutional Neural Networks (CNN).
- Hybrid Architectures.

Interpretability

- Transparency.
- Post-Hoc Interpretability.
  - Class Activation Methods.
- Evaluating Interpretability.

Preliminaries

Approaching Vision

Preliminaries

David Marr's approach

Addressing vision on three levels:

- Algorithmic.
- Implementation.
- Computational.
  - Three fundamental tasks. [1]

Preliminaries

David Marr’s approach

Addressing vision on three levels:

- Algorithmic.
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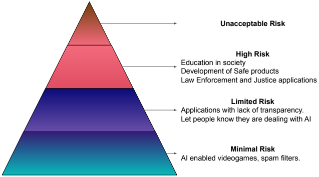
Computer Vision focuses on the last level.

Preliminaries

CV Currently

Preliminaries

Desiredata of Interpretability Study



Unacceptable Risk

High Risk
Education in society
Development of Safe products
Law Enforcement and Justice applications

Limited Risk
Applications with lack of transparency.
Let people know they are dealing with AI

Minimal Risk
AI enabled videogames, spam filters.

Image Recognition Models

Classic Models

Image Recognition Models

Convolutional Neural Networks

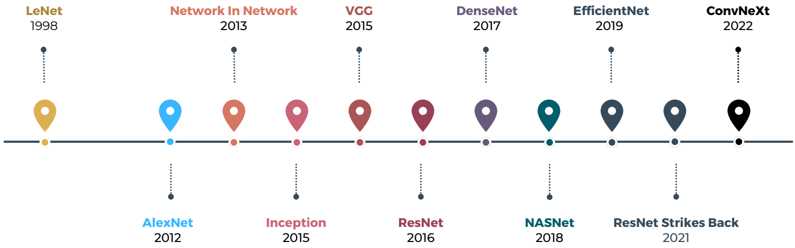


Image Recognition Models

Self Attention Architectures

Image Recognition Models

Hybrid Architectures

Interpretability

Transparency

Interpretability

Post-Hoc Interpretability

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Class Activation Methods

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Evaluating Interpretability

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- J. McCarthy *et al.*, “What is artificial intelligence,” 2007.