

Unsupervised Decomposition of Images into Motifs

Décomposition non supervisée d'images en sous-motifs

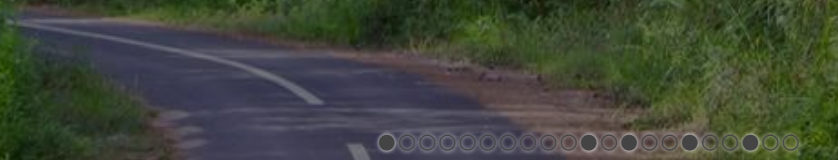
2022-06-16

Rémi EMONET

Atelier « Enjeux et méthodes d'analyse d'ornements anciens »

Avertissement

Avertissement



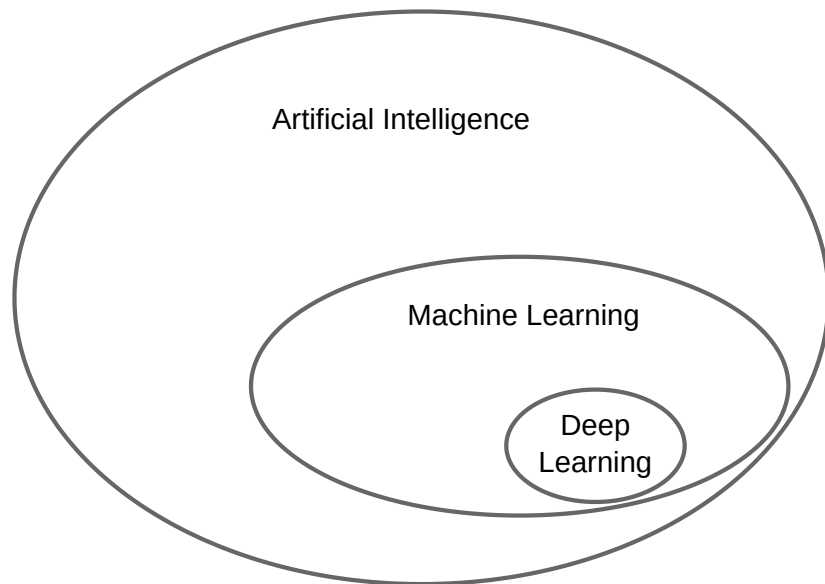
Overview

- Different Flavors of Machine Learning
- Why Looking for Sub-Motifs
- Decomposing Spatio-Temporal Data Using Probabilistic Models
- Towards "Modern" Approaches to Decomposition
- Summary and Conclusions

Different Flavors of Machine Learning

Le « Machine Learning » et ses multiples facettes

Artificial Intelligence / Machine Learning / Deep Learning



Software design and its limitation

Écriture de logiciels et ses limitations

- Traditional software
 - a developer write a program
 - i.e., a set of instructions that the computer understands
 - i.e., very elementary operations or more complex ones, written beforehand
 - the instructions (should) solve the task of interest
 - given some input, the computer applies the instructions, a result is produced
- Limitations: the developer is not a domain expert, and vice versa
 - also, translating human knowledge/intuition into a program might be difficult
 - e.g., what does it mean to find a cat in a picture?
- Expert systems
 - encode expert knowledge in a database
 - write a (more) generic program that uses this database

Supervised Machine Learning

Apprentissage automatique supervisé

- Limitation of traditional and expert systems
 - reminder: write a program and/or expert knowledge
 - encoding expert knowledge is time consuming
 - choosing the proper knowledge representation is very difficult
 - formalizing the knowledge might be close to impossible
- *Supervised machine learning*: principle
 - use a *labeled dataset* with
 - some example inputs (e.g. images)
 - for each input, the associated expected output (label) (e.g. whether it is a cat or not)
 - just labels, no analysis of the expert knowledge
 - apply a (machine learning) algorithm/program, which
 - inputs the whole labeled dataset
 - outputs a *model* that can automatically affect a label to a new input (a model $\approx$ a program)

Supervised Machine Learning, creating a dataset



, Cat



, NonCat



, Cat



, Cat



, NonCat



, Cat



, Cat



, NonCat

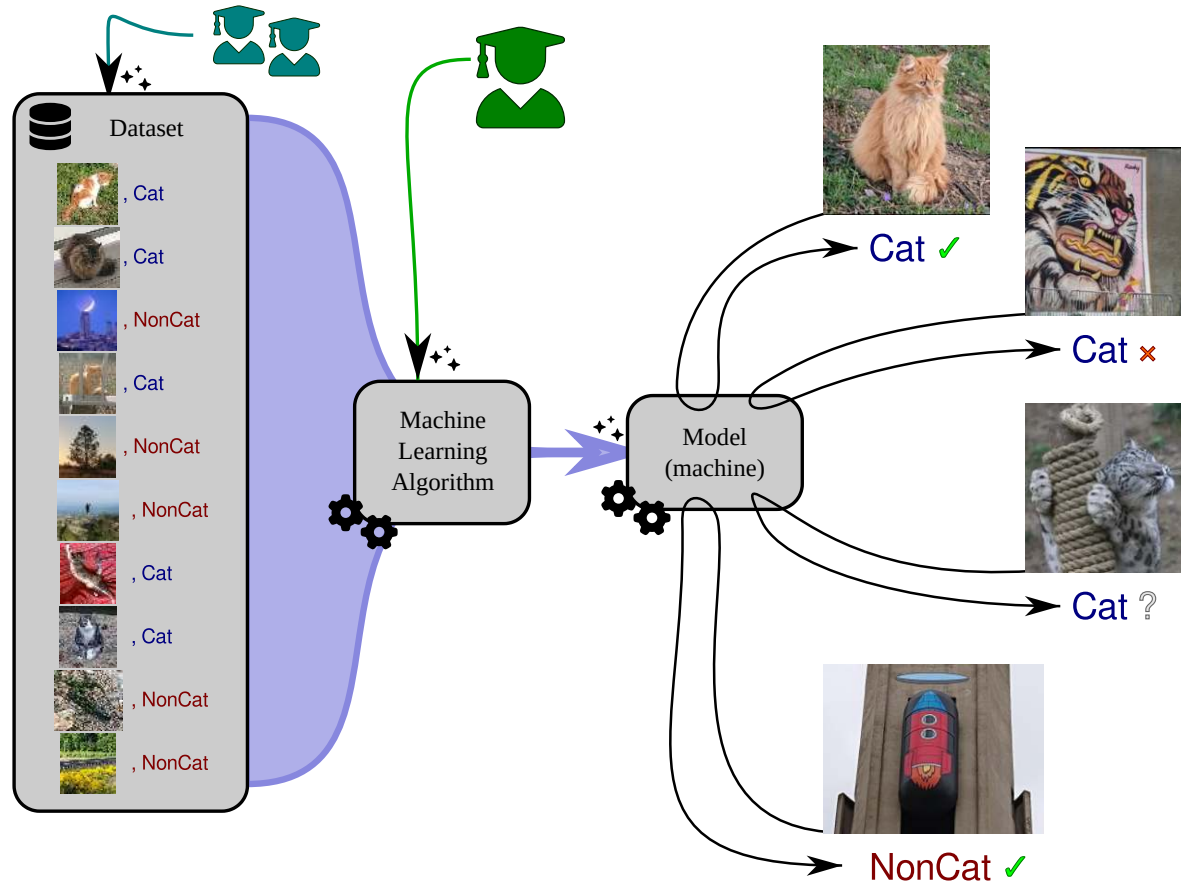


, NonCat



, NonCat

Supervised Machine Learning, illustrated



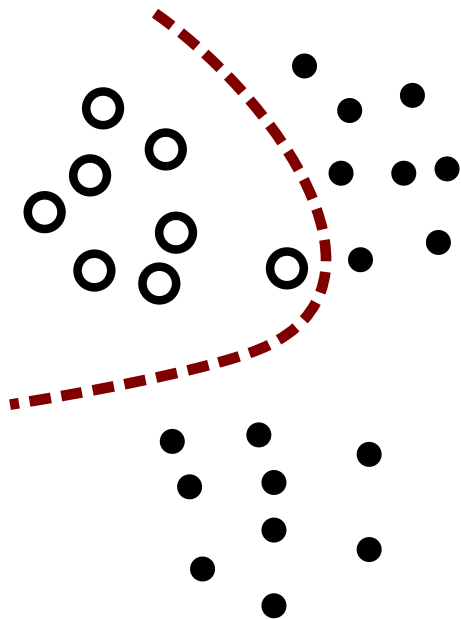


Many Applications of Supervised Learning

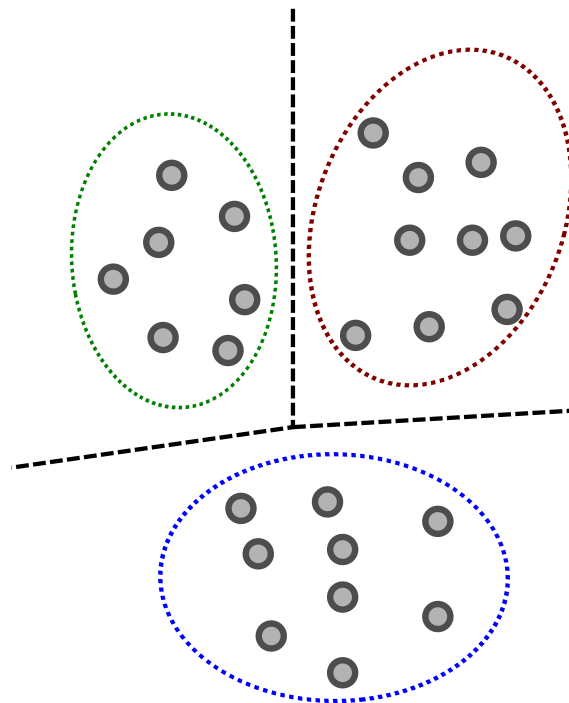
- Image classification and search,
- Automated translation,
- Spam detection,
- ...
- Text/Banner/Ornament segmentation (pixel classification)
- Localization of (known) vignettes (bounding box detection)

Supervised (known labels)	Unsupervised (only inputs)
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Supervised
(known labels)



Unsupervised (only inputs)



Other Machine Learning Setups

- supervised
- semi-supervised
- weakly supervised
- self supervised
- active learning
- reinforcement learning

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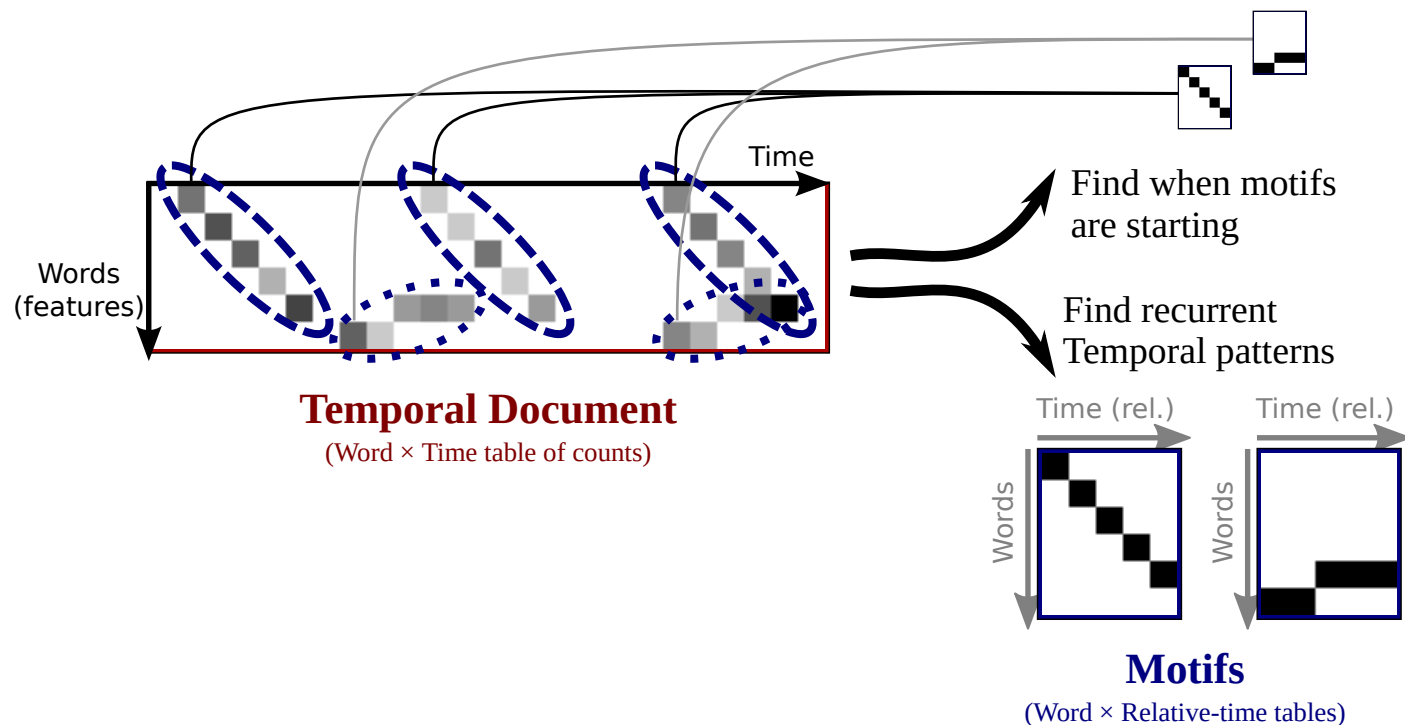
Why Looking for Sub-Motifs

Pourquoi de la Recherche de (sous-)motifs

Decomposing Spatio-Temporal Data Using Probabilistic Models

Décomposition de données spatio-temporelles avec des modèles probabilistes

Finding Temporal Motifs in videos / temporal data (spectrograms, ...)



Principle of Probabilistic Modeling (generative models)

Modèles Probabilistes Génératifs

- Generative story
 - assumptions
 - expert intuition
 - may be difficult
- Challenges
 - encode knowledge as structure
 - derive/write the optimization algorithm
 - ... jointly

Towards "Modern" Approaches to Decomposition

Vers les Approches Modernes de Décomposition

Deep Learning Approaches to Decomposition

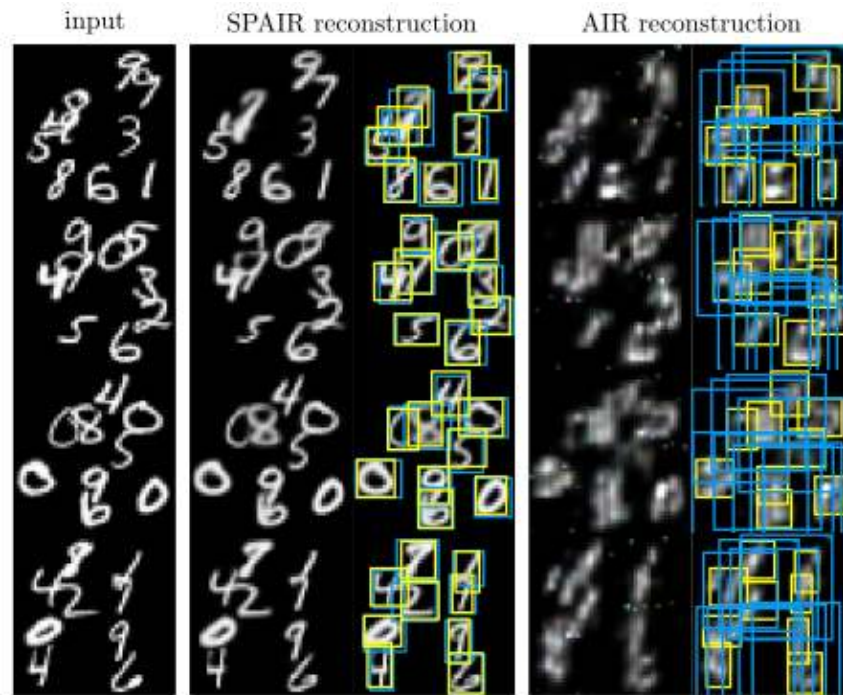
Apprentissage Profond pour la Décomposition

- Use "Deep Learning" approaches
 - gives more flexibility when encoding knowledge as structure
 - directly reuse the optimization algorithm
 - but, usually require more data

Some recent approaches

Quelques nom d'approches récentes

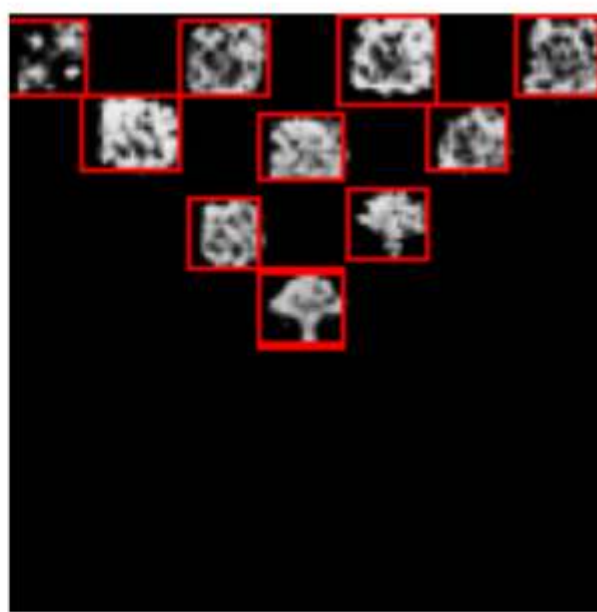
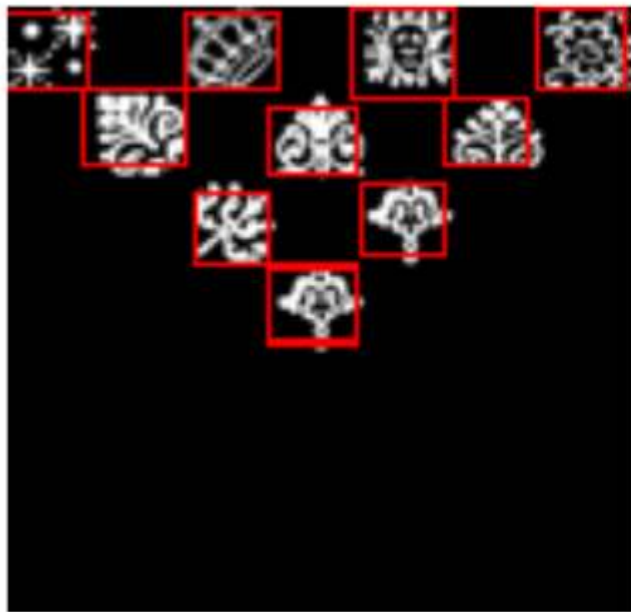
- AIR (2016), SPAIR (2018)
- IODINE, GENESIS
- DAIR, SQAIR, R-SQAIR
- SPACE
- RICH (2020)
- ...



First Explorations with Ornaments

Some Results: on an image with similar vignettes

Résultat: exemple sur une images avec des vignettes similaires



Some Results: on an image with unseen vignettes

Résultat: exemple sur une images avec des vignettes nouvelles



Possible Outcomes

Résultats (futurs) éventuellement possibles

- To be expected
 - decomposing unlabeled datasets of composite ornaments
 - grouping (and showing) similar vignettes
 - highlighting differences,
 - suggest hierarchical aggregations of vignettes
- Open questions
 - decomposing "passe-partout"
 - integrating/infering metadata
 - print date, official address, official printer,
 - ... and actual ones
 - "alphabet" available at given workshop
 - inferring/integrating "latent" information
 - vignette rotation (90°, 180°)
 - aging of woods/vignettes
 - pressing style or intensity, inking
 - learning the composition style (need more data?)

Summary and Conclusions



Take-Home Message

- Machine Learning uses data to automatically write programs
- Supervised Learning is amazing and is used a lot
- Unsupervised Learning is challenging but also amazing
- Decomposing images in recurrent motifs might be useful for composite ornaments