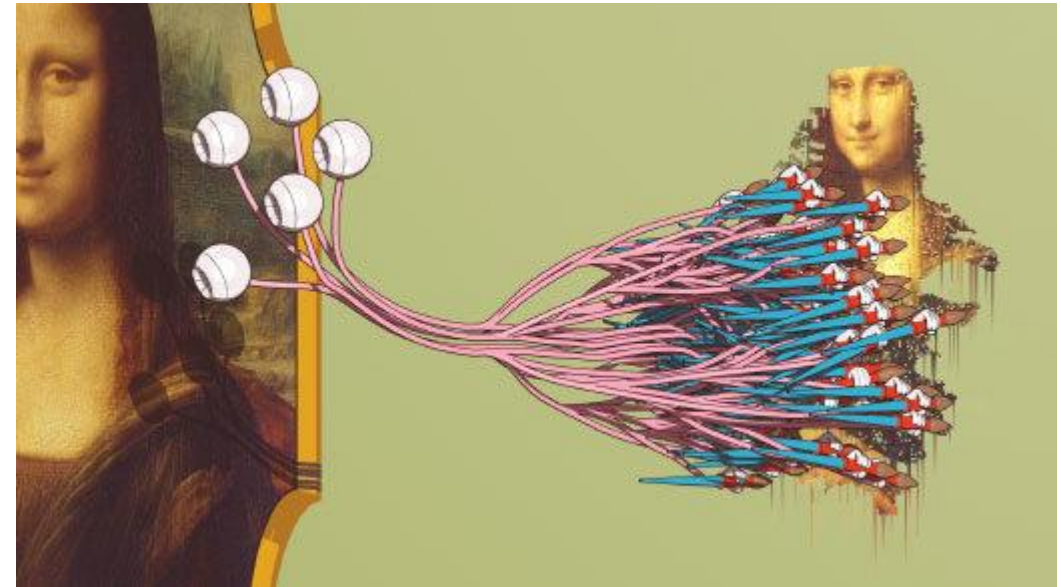


MonaLIA 2.0

*Fusion of deep learning and semantic reasoning
for image recognition and enrichment of
Joconde database metadata*



[DVDP](#) for Quanta Magazine

Motivation to Enrich Joconde Database



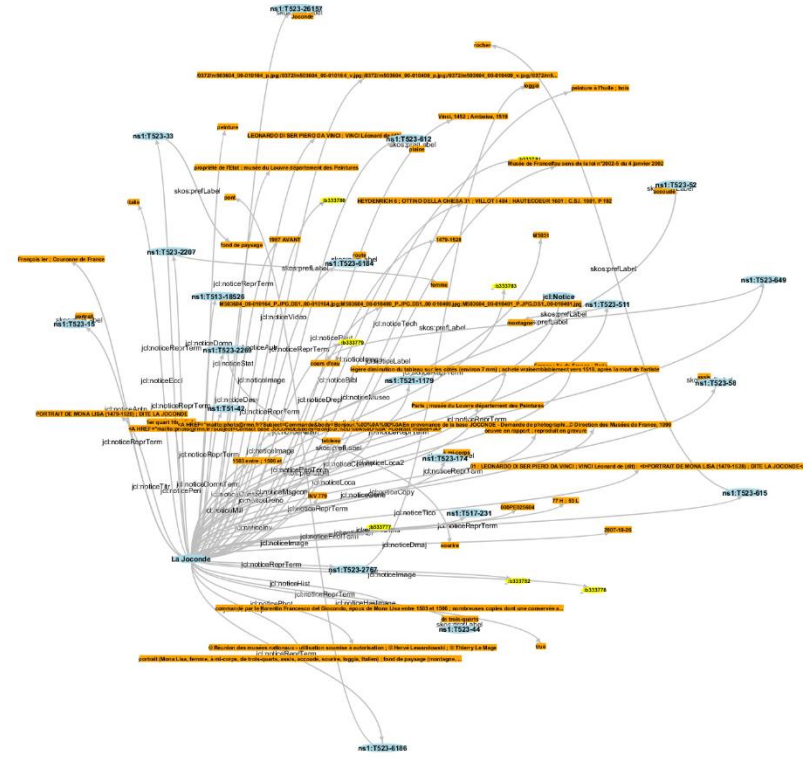
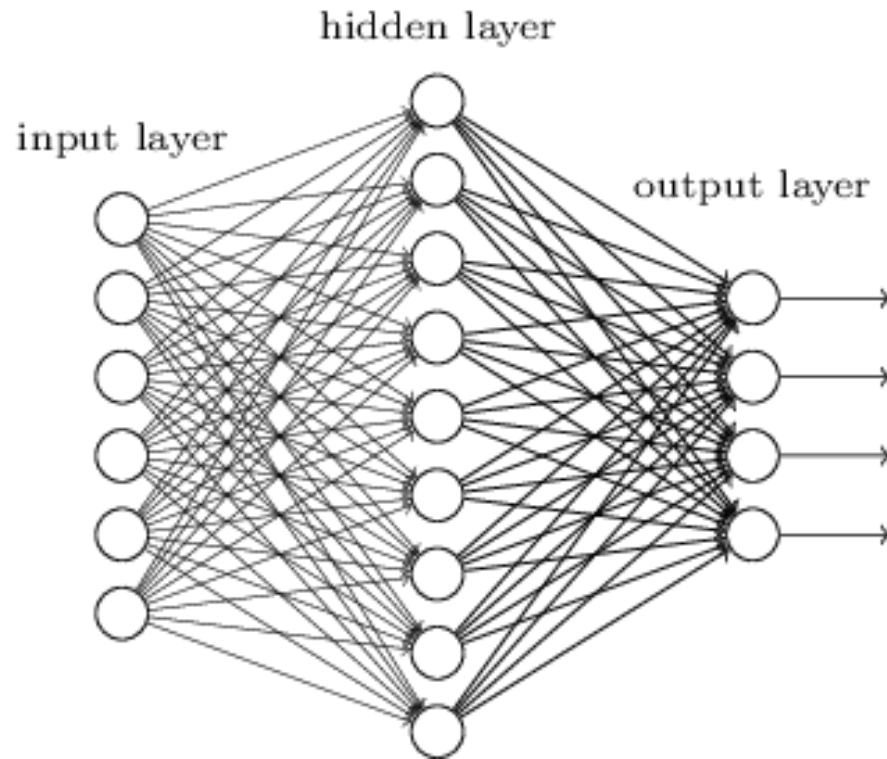
PORTRAIT DE MONA LISA (1479-1528) ; DITE LA JOCONDE by
Leonardo Da Vinci
© Musée du Louvre, © Direction des Musées de France, 1999

- ~300 000 illustrated artwork records from the French museums.
- RDF metadata about the artwork content and properties (media, author, museum, etc.).
- content metadata is organized according to Thesaurus Iconographique (Francois Garnier, 1981)
- **Can the digital artwork collections be automatically enhanced by combining Machine Learning and Knowledge Representation & Reasoning?**
- **Can annotation of the artworks be automated or semi-automated?**
- **Can the search results be ranked by the visual relevancy of a search criteria?**

Combining Strength of Two Methods

Deep Learning from unstructured data such as images

Semantic Reasoning and querying from semantic metadata

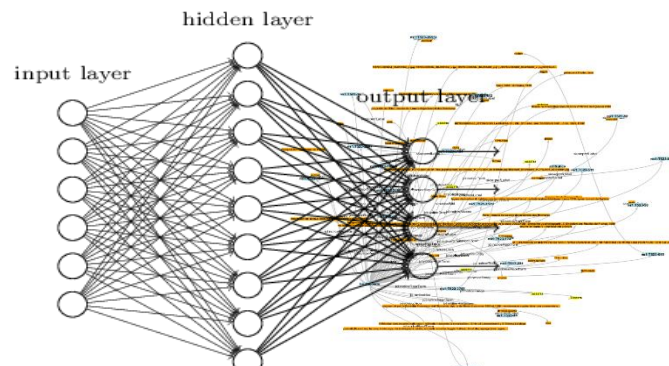


Combining Strength of Two Methods

Deep Learning from unstructured data such as images

Semantic Reasoning and querying from semantic metadata

- reason to **prepare training and validation sets** & labels



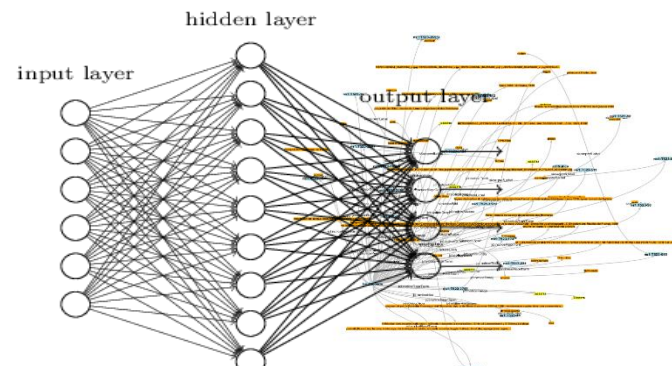
Combining Strength of Two Methods

Deep Learning from unstructured data such as images

- learn to classify image content to **annotate artworks** with efficiency

Semantic Reasoning and querying from semantic metadata

- reason to **prepare training and validation sets** & labels



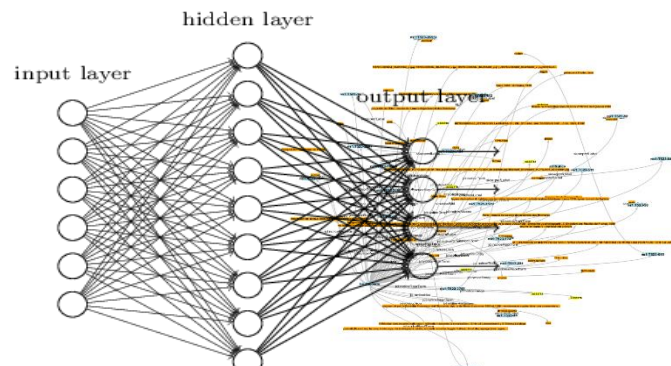
Combining Strength of Two Methods

Deep Learning from unstructured data such as images

- learn to classify image content to **annotate artworks** with efficiency

Semantic Reasoning and querying from semantic metadata

- reason to **prepare training and validation sets** & labels
- reason to **extend quality of the metadata** that is incomplete or noisy



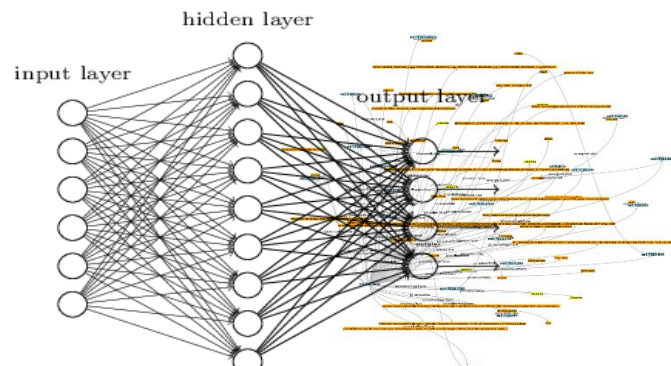
Combining Strength of Two Methods

Deep Learning from unstructured data such as images

- learn to classify image content to **annotate artworks** with efficiency
- learn to **extend the existing metadata** with quantitative measures of object relevance

Semantic Reasoning and querying from semantic metadata

- reason to **prepare training and validation sets** & labels
- reason to **extend quality of the metadata** that is incomplete or noisy



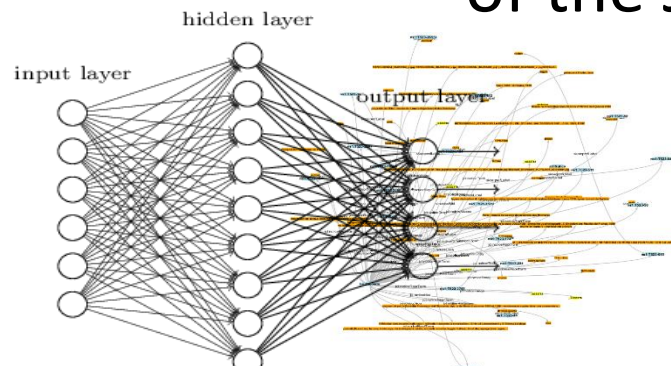
Combining Strength of Two Methods

Deep Learning from unstructured data such as images

- learn to classify image content to **annotate artworks** with efficiency
- learn to **extend the existing metadata** with quantitative measures of object relevance

Semantic Reasoning and querying from semantic metadata

- reason to **prepare training and validation sets** & labels
- reason to **extend quality of the metadata** that is incomplete or noisy
- reason to **improve searchability** of the Joconde database



Conclusions of MonaLIA 1.0

- Deep Learning Transfer works even from non cultural collections
 - The model gives good accuracy results even on the object categories that it hadn't been pre-trained on.
- The limitations are mostly from the labeled image availability.
 - Adding images from other museum collections and Wikipedia can increase the training set.
- Joconde database metadata can be improved by filling the missing values and structuring some fields
 - Missing values can be inferred by machine learning algorithms.
 - Introducing the ontologies on techniques, material, denomination, preservation state can help to deeper explore the relations between all possible structured representations

MonaLIA 2.0 Approach

- SPARQL+RDFS+SKOS on metadata to extract training and test subsets of images
- Train Multi-Label Deep Learning classifier
- Apply trained model and extend metadata
- SPARQL on extended metadata to search the database

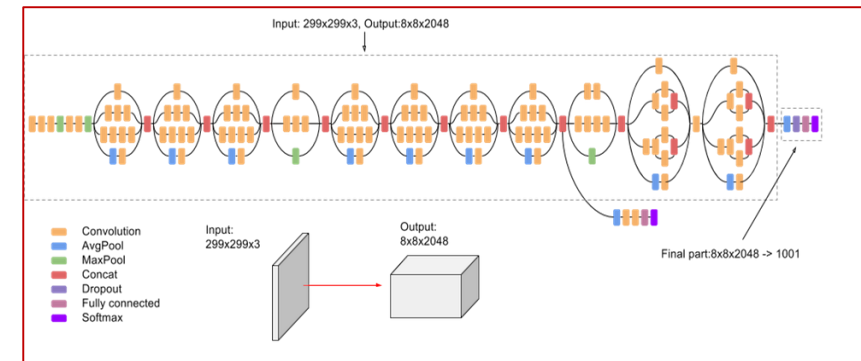
```
prefix skos: <http://www.w3.org/2004/02/skos/core#>
prefix jcl: <http://jocondelab.iri-research.org/ns/jocondelab/>

select (replace(group_concat(?topCategory_label; separator="+", "\\|+$", "")) as ?label)
  (sample(?noticeRepresentation) as ?repr)
  (sample(?imagePath) as ?image_path)
  (sample(?noticeReference) as ?ref)
where
{
  values (?topCategory_label) { ("chien"@fr) ("cheval"@fr) }.

  ?topCategory a jcl:Term;
               skos:prefLabel ?topCategory_label;
               skos:narrower* | skos:related/skos:narrower* ?subCategory.

  ?subCategory skos:prefLabel ?subCategory_label.

  ?notice jcl:noticeReprTerm ?subCategory;
          jcl:noticeHasImage true;
          jcl:noticeRef ?noticeReference.
}
group by ?noticeReference
```



```
@prefix rdfs: <http://www.w3.org/2000/01/rdf-schema#> .
@prefix jcl: <http://jocondelab.iri-research.org/ns/jocondelab/> .
@prefix t: <http://data.culture.fr/thesaurus/resource/ark:/67717/> .
@prefix ml: <http://ns.inria.fr/monalia/> .

ml:classifiedSubject a rdfs:Class ;
ml:classified40_classes rdfs:label "40_classes" ;
rdfs:subClassOf ml:classifiedSubject .

<https://jocondelab.iri-research.org/data/notice/00000055013> ml:imageClassifier [ a
ml:classified40_classes ;
ml:detected [ a t:T523-6519 ; ml:score 0.8102 ],
             [ a t:T523-6209 ; ml:score 0.0219 ],
             [ a t:T523-175 ; ml:score 0.3843 ],
             ...
             [ a t:T523-2037 ; ml:score 0.0121].
```

MonaLIA 2.0 Approach

- SPARQL+RDFS+SKOS on metadata to extract training and test subsets of images
 - label training and test sets including the “narrower” categories according to Garnier Thesaurus
 - create “missing” links between some categories
 - balance number of training images per class
 - filter out certain categories and images
- Train Multi-Label Deep Learning classifier
- Apply trained model and extend metadata
- SPARQL on extended metadata to search the database

```
prefix skos: <http://www.w3.org/2004/02/skos/core#>
prefix jcl: <http://jocondelab.iri-research.org/ns/jocondelab/>

select (replace(group_concat(?topCategory_label; separator="+", "\\|+$", "")) as ?label)
  (sample(?noticeRepresentation) as ?repr)
  (sample(?imagePath) as ?image_path)
  (sample(?noticeReference) as ?ref)
where
{
  values (?topCategory_label) { ("chien"@fr) ("cheval"@fr) }.

  ?topCategory a jcl:Term;
               skos:prefLabel ?topCategory_label;
               skos:narrower* | skos:related/skos:narrower* ?subCategory.

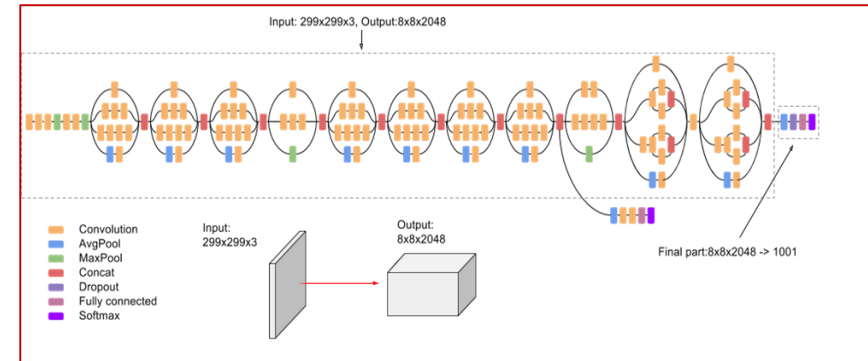
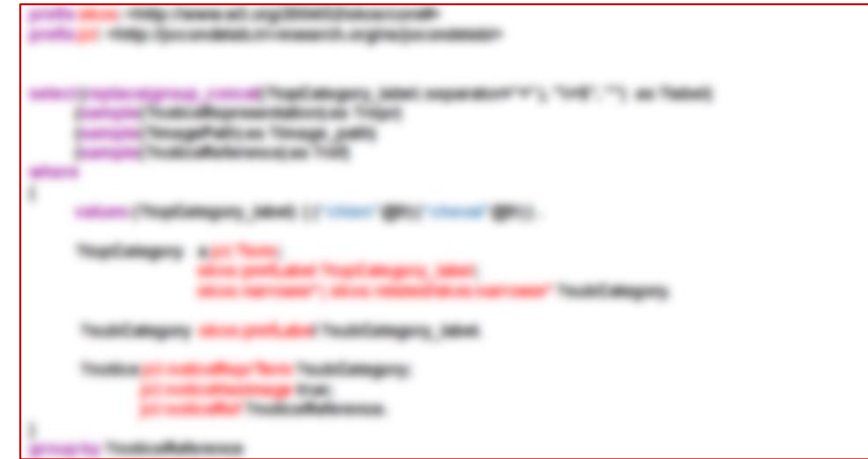
  ?subCategory skos:prefLabel ?subCategory_label.

  ?notice jcl:noticeReprTerm ?subCategory;
          jcl:noticeHasImage true;
          jcl:noticeRef ?noticeReference.
}
group by ?noticeReference
```



MonaLIA 2.0 Approach

- SPARQL+RDFS+SKOS on metadata to extract training and test subsets of images
 - create labeled training and test sets including the “narrower” categories according to Garnier Thesaurus
 - create “missing” links between some categories
 - balance number of training images per class
 - filter out certain categories and images
- Train Multi-Label Deep Learning classifier
 - select state-of-the-art pre-trained CNN model
 - adapt the model to multi-label classification
 - fine-tune model on labeled training sets
 - optimize model hyperparameters for best performance
- Apply trained model and extend metadata
 - run all the images through the trained classifier
 - record the prediction score as RDF triples
- SPARQL on extended metadata to search the database



MonaLIA 2.0 Approach

- SPARQL+RDFS+SKOS on metadata to extract training and test subsets of images
 - create labeled training and test sets including the “narrower” categories according to Garnier Thesaurus
 - create “missing” links between some categories
 - balance number of training images per class
 - filter out certain categories and images
- Train Multi-Label Deep Learning classifier
 - select state-of-the-art pre-trained CNN model
 - adapt the model to multi-label classification
 - fine-tune model on artwork images
 - optimize model hyperparameters for best performance
- Apply trained model and extend metadata
 - run all the images through the trained classifier
 - record the prediction score as RDF triples
- SPARQL on extended metadata to search the database

```
SPARQL query snippet showing metadata extraction and filtering.
```



```
@prefix rdfs: <http://www.w3.org/2000/01/rdf-schema#>.
@prefix jcl: <http://jocondelab.iri-research.org/ns/jocondelab/>.
@prefix t: <http://data.culture.fr/thesaurus/resource/ark:/67717/>.
@prefix ml: <http://ns.inria.fr/monalia/>.

ml:classiferRepresentedSubject a rdfs:Class;
ml:classifer40_classes rdfs:label "40_classes";
rdfs:subClassOf ml:classiferRepresentedSubject .

<https://jocondelab.iri-research.org/data/notice/00000055013> ml:imageClassifier [ a
ml:classifer40_classes;
ml:detected [ a t:T523-6519; ml:score 0.8102 ],
[ a t:T523-6209; ml:score 0.0219 ],
[ a t:T523-175; ml:score 0.3843 ],
...
[ a t:T523-2037; ml:score 0.0121].
```

MonaLIA 2.0 Approach

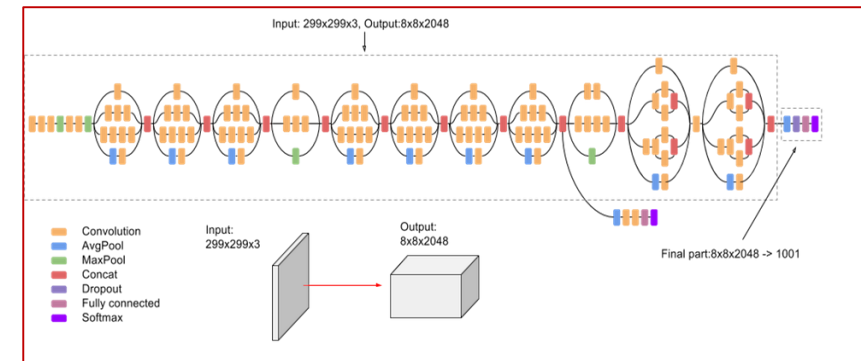
- SPARQL+RDFS+SKOS on metadata to extract training and test subsets of images
 - create labeled training and test sets including the “narrower” categories according to Garnier Thesaurus
 - create “missing” links between some categories
 - balance number of training images per class
 - filter out certain categories and images
- Train Multi-Label Deep Learning classifier
 - select state-of-the-art pre-trained CNN model
 - adapt the model to multi-label classification
 - fine-tune model on artwork images
 - optimize model hyperparameters for best performance
- Apply trained model and extend metadata
 - run all the images through the trained classifier
 - record the prediction score as RDF triples
- SPARQL on extended metadata to search the database

```
prefix skos: <http://www.w3.org/2004/02/skos/core#>
prefix jcl: <http://jocondelab.iri-research.org/ns/jocondelab/>

select (replace(group_concat(?topCategory_label; separator="+", "\\|+$", "") as ?label)
       (sample(?noticeRepresentation) as ?repr)
       (sample(?imagePath) as ?image_path)
       (sample(?noticeReference) as ?ref)
where
{
  values (?topCategory_label) { ("chien"@fr) ("cheval"@fr) }.
  ?topCategory a jcl:Term;
               skos:prefLabel ?topCategory_label;
               skos:narrower* | skos:related/skos:narrower* ?subCategory.

  ?subCategory skos:prefLabel ?subCategory_label.

  ?notice jcl:noticeReprTerm ?subCategory;
          jcl:noticeHasImage true;
          jcl:noticeRef ?noticeReference.
}
group by ?noticeReference
```

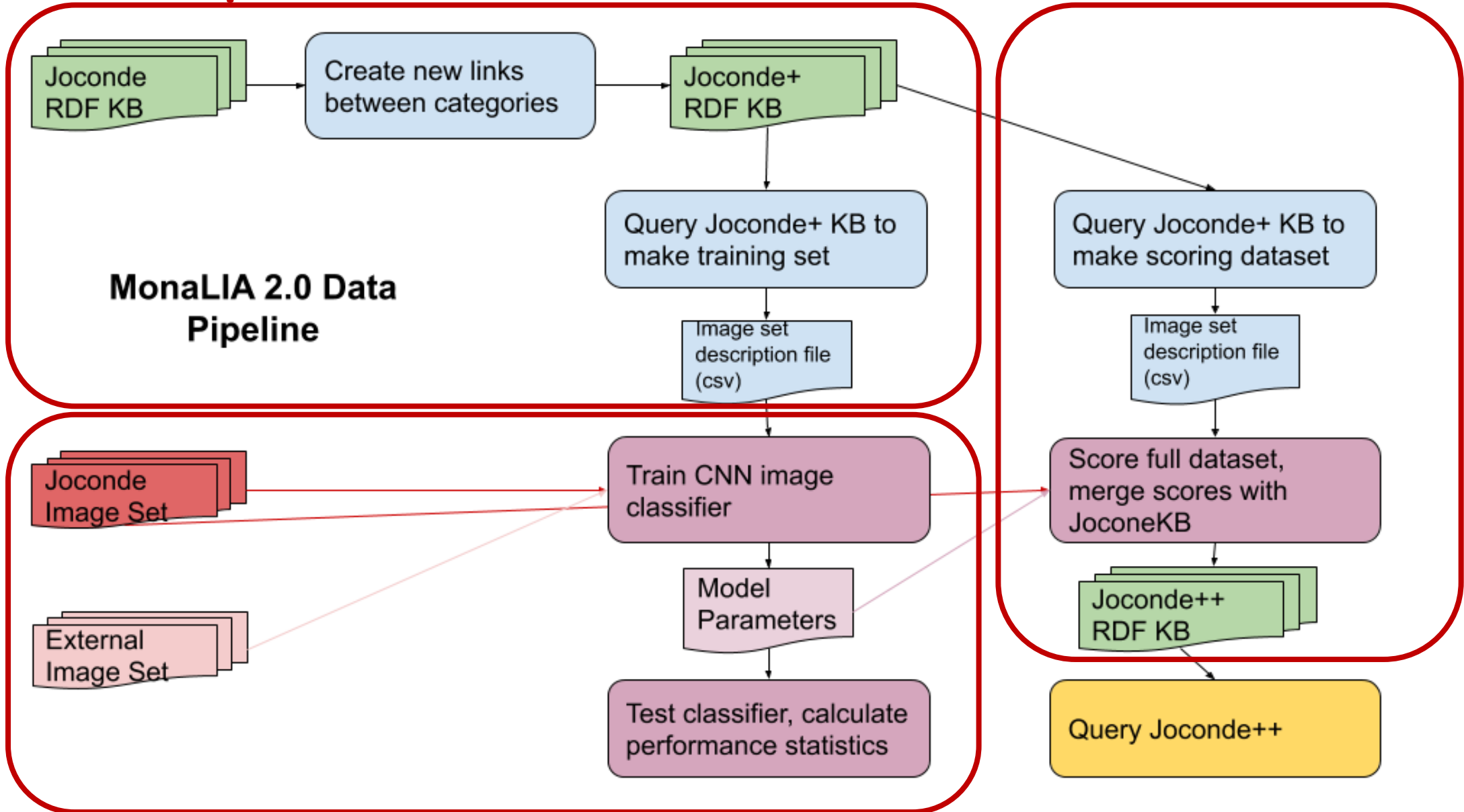


```
@prefix rdfs: <http://www.w3.org/2000/01/rdf-schema#>.
@prefix jcl: <http://jocondelab.iri-research.org/ns/jocondelab/>.
@prefix t: <http://data.culture.fr/thesaurus/resource/ark:/67717/>.
@prefix ml: <http://ns.inria.fr/monalia/>.

ml:classifierRepresentedSubject a rdfs:Class; ml:vocabID "REPR".
ml:classifier40_classes rdfs:label "40_classes";
rdfs:subClassOf ml:classifierRepresentedSubject.

<https://jocondelab.iri-research.org/data/notice/00000055013> ml:imageClassifier [ a ml:classifier40_classes;
ml:detected [ a t:T523-6519; ml:score 0.8102 ],
[ a t:T523-6209; ml:score 0.0219 ],
[ a t:T523-175; ml:score 0.3843 ],
...
[ a t:T523-2037; ml:score 0.0121].
```


Data Pipeline



Linking Related Categories



Lévrier tenant un lièvre dans sa gueule by Pierre Jules Méné
© musée de la Vénerie ; Senlis, © Direction des Musées de France, 2009

Sujet représenté figure (Révolution française de 1848, soldat, cavalier, cheval, uniforme)

- Not all semantically similar categories are linked by Garnier Thesaurus (e.g. humans on the images not necessarily annotated by the terms in the “être humain” @fr hierarchy)
- Poor labeling -> poor model performance
- New RDF triples to link the categories that are not linked by the hierarchical thesaurus

```
@prefix skos: <http://www.w3.org/2004/02/skos/core#> .
```

```
insert { ?x skos:related ?y }
```

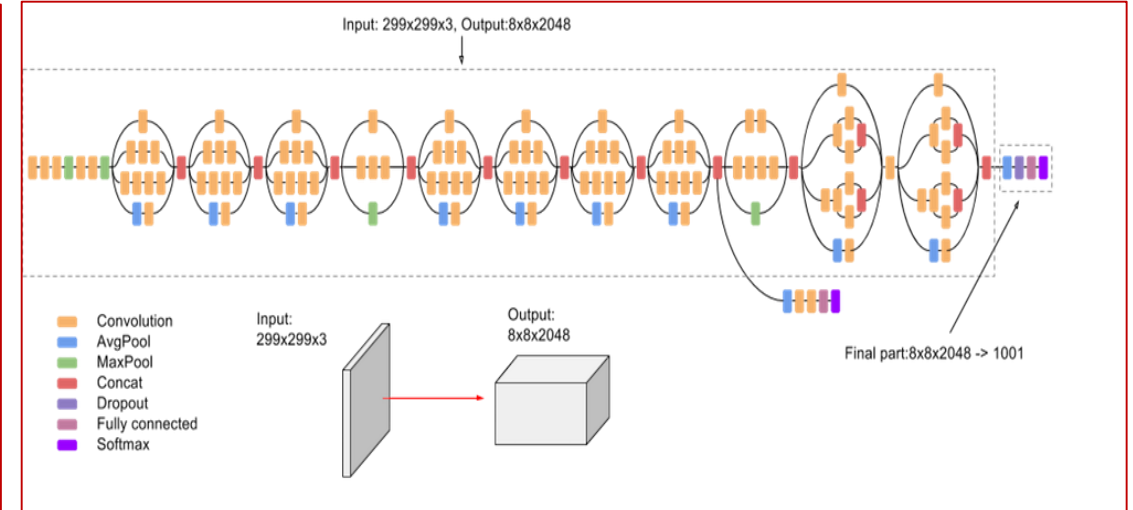
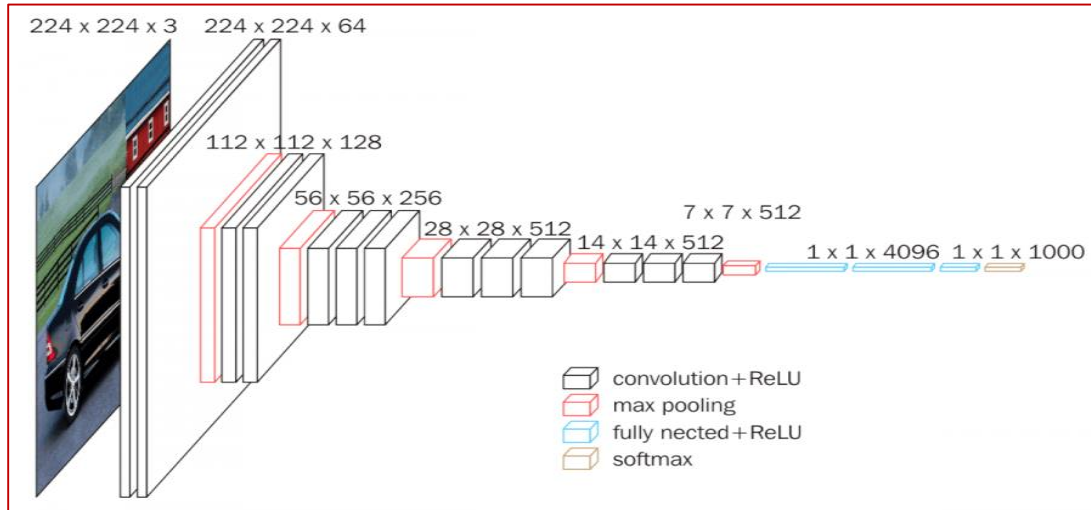
```
where {
```

```
    ?x skos:prefLabel "être humain" @fr.
```

```
    ?y skos:prefLabel "hiérarchie militaire" @fr.
```

```
}
```

Selecting Multi-label Classification Model



- VGG16 model
- 1st Runner-Up in ILSVRC2014
- 10 classes mAP = 0.78
- ~138 million parameters
- ~525 MB disk space
- 3h35m training time*

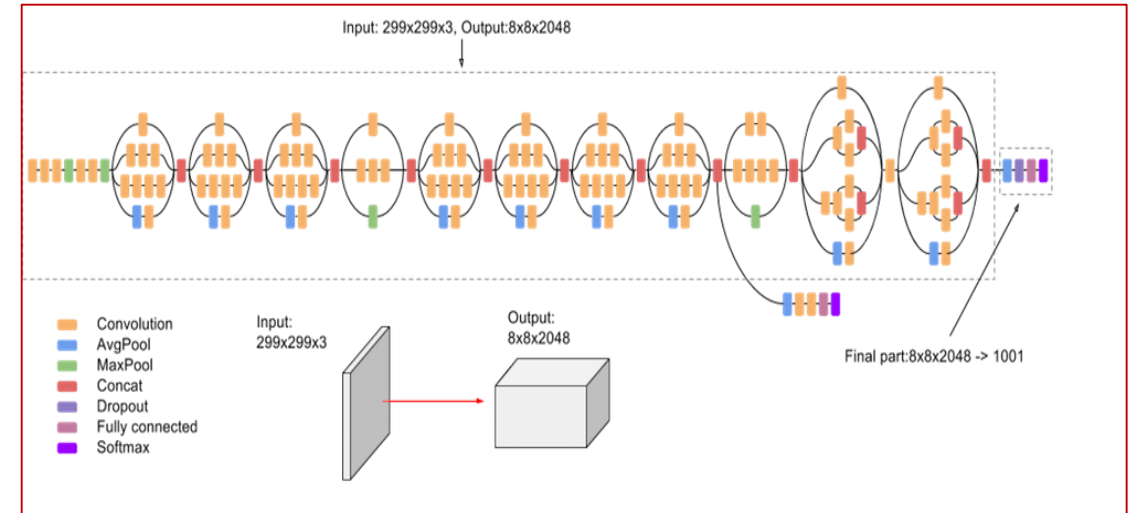
- Inception v3 model
- Inception v1 is a Winner in ILSVRC2014
- 10 classes mAP = 0.79
- ~4 million parameters
- ~96 MB disk space
- 3hr15m training time*

* Training time is benchmarked on 40 class multi-label classifier, 55 900 training samples on cluster node with 2x Xeon SP Gold 5115 @ 2.4 GHz CPU, 256 GB RAM with 2 GeForce GTX 1080 Ti GPUs cards connected with a PCIe gen3 16x interface, 11GB of RAM per card.

Tuning Classification Model for Best Performance

Hyperparameters

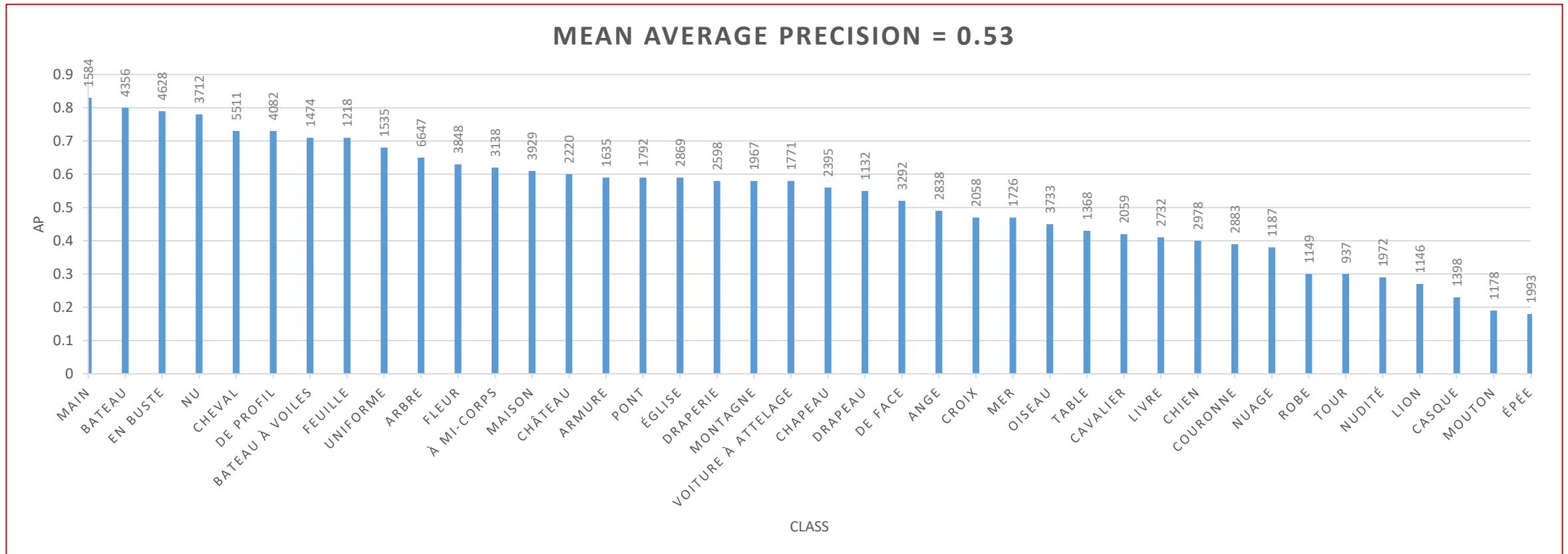
- Training mode: fine-tuning
- Dropout rate: 0.5
- Activation function: sigmoid
- Loss Function: Binary Cross Entropy
- Optimizer: Adam
- Initial learning rate: 0.001
- Training epochs: 20
- Learning rate decay schedule: reduce by 0.1 every 4 epochs
- Momentum : 0.9



- Inception v3 model
- Inception v1 in a Winner in ILSVRC2014
- ~4 million parameters
- ~95 MB disk space
- 3hr15m training time

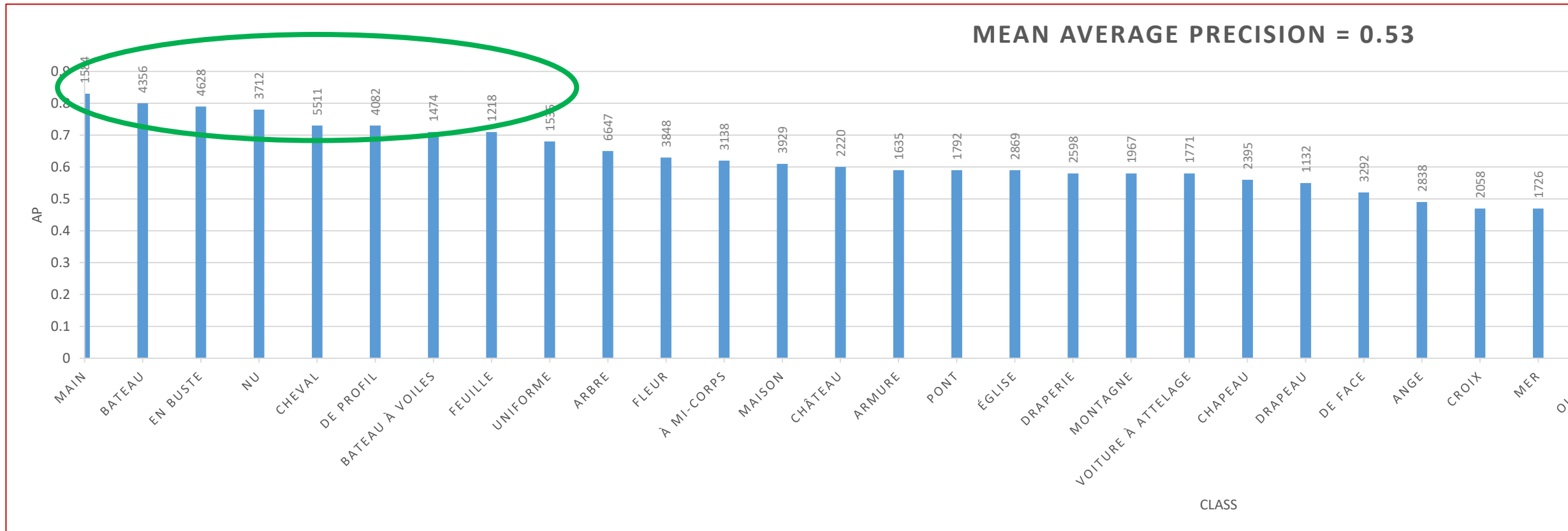
Multi-label Model Performance

- 40-class multi-label classifier
 - 40 of 100 categories from the Ministry of Culture list have adequate number of images for training



Multi-label Model Performance

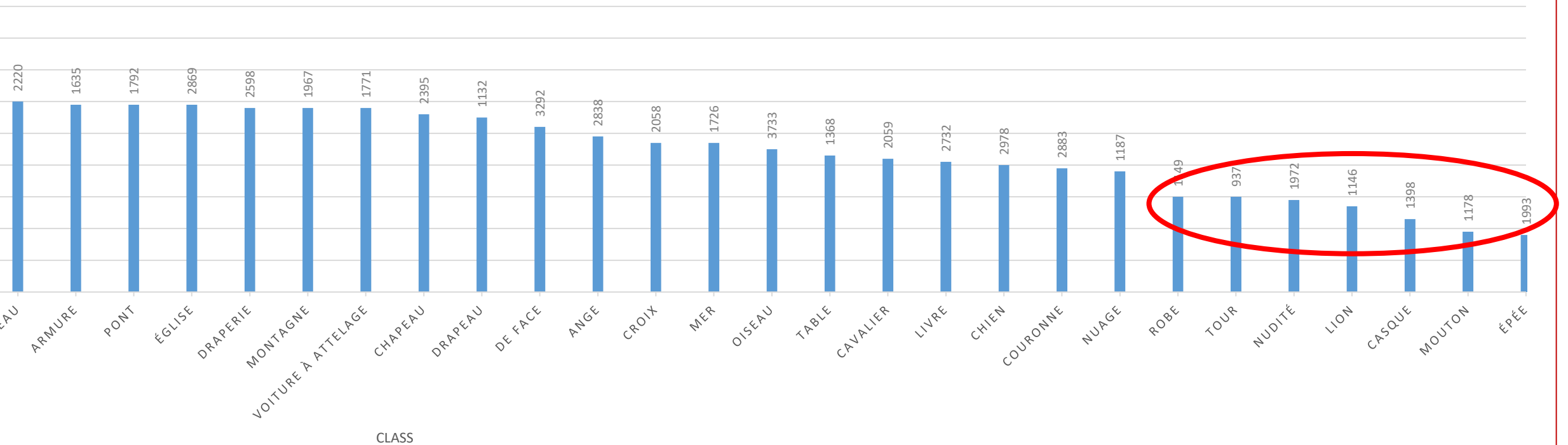
- Some categories are easier to detect
 - general categories
 - large object



Multi-label Model Performance

- Some categories are harder to detect
 - relatively small objects
 - visually close to more prevalent categories

MEAN AVERAGE PRECISION = 0.53



Extending Training Image Set



- One of the limitations of object detection is labeled image availability
- 60 categories out of 100 from the Ministry of Culture list have insufficient number of images to train machine learning algorithms
- More contemporary objects are less represented
- Exploring other museum collections to increase the training set

Study for Transportation Mural by
William Sommer

© Cleveland Museum of Art, 2019

Extending Training Image Set



Study for Transportation Mural by William Sommer

© Cleveland Museum of Art, 2019

- One of the limitations of object detection is labeled image availability
- 60 categories out of 100 from the Ministry of Culture list have insufficient number of images to train machine learning algorithms
- More contemporary objects are less represented
- Exploring other museum collections to increase the training set

Collection	API	Number of available images	Number of labeled images
The Behance Artistic Media Dataset	SQLITE HTTP	78 687	8 338
Pinterest	HTTP		641
Cleveland Museum of Art	CSV HTTP	30 676	1 283
Smithsonian Museums: American Art Museum	SPARQL HTTP	3 900 000 (site) 47 133 (SPARQL)	In progress

Generate & Query Extended Metadata

- Apply model to all images
 - classifier outputs prediction scores per category per image
- Extend metadata with prediction scores
 - store in RDF format
 - linked to artwork records
- SPARQL query on
 - object(s) +
 - classifier(s) +
 - prediction score

```
prefix skos: <http://www.w3.org/2004/02/skos/core#>
prefix jcl: <http://jocondelab.iri-research.org/ns/jocondelab/>
prefix ml: <http://ns.inria.fr/monalia/>

select ?searchCategory_label ?searchScore_value ?ref ?title ?repr
?score ?imagePath
where {
    ?searchCategory a jcl:Term;
                    skos:prefLabel "chien"@frr.




    ?classifier rdfs:subClassOf/ml:vocabID "REPR";
               rdfs:label "40_classes".

    ?notice jcl:noticeRef ?ref;
            jcl:noticeTitr ?title;
            jcl:noticeRepr ?repr;
            jcl:noticeImage [ jcl:noticeImageIsMain true ;
jcl:noticeImagePath ?imagePath];
            ml:imageClassifier [a ?classifier ; ml:detected [a
?searchCategory; ml:score ?score]] .

    filter ( ?score >= 0.90 )
}
order by desc(?score)
```




Detecting “noise”

- By querying the extended metadata for the objects with low scores we can detect the “noise” in the represented subject annotation

Image	Metadata	Score
	<p>figure (saint Eloi de Noyon, évêque, en pied, bénédiction, vêtement liturgique, mitre, attribut, cheval, marteau, outil : ferronnerie)</p> <p>000SC022652</p> <p>C:/Joconde/joconde\0355/m079806_bsa0030101_p.jpg</p>	cheval: 0.006
	<p>figures bibliques (Vierge à l'Enfant, à mi-corps, assis, Enfant Jésus : nu, livre);fond de paysage (colline, cours d'eau, barque, cavalier)</p> <p>000PE027041</p> <p>C:/Joconde/joconde\0001/m503604_90ee1719_p.jpg</p>	cheval: 0.009
	<p>scène (satirique : Bismarck Otto von : Gargantua, repas, cheval, boisson : vin)</p> <p>5002E006121</p> <p>C:/Joconde/joconde\0074/m500202_atpico-g70128_p.jpg</p>	cheval: 0.011

Detecting “silence”

- By querying the extended metadata for the object with high scores and without object mentioned in annotation we can detect the “silence” in the annotation

Image	Metadata	Score
	portrait 50350012455 C:\Joconde\joconde\0138\m503501_d0012455-000_p.jpg	cheval: 0.999
	scène historique (guerre de siège : Lawfeld, Louis XV, Saxe maréchal de, bataille rangée) 000PE004371 C:\Joconde\joconde\0634\m507704_79ee519_p.jpg	cheval: 0.999
	figure (sainte Jeanne d'Arc, jeune fille, équestre passant, armure, asque, épée) M0301000355 C:\Joconde\joconde\0617\m030106_007305_p.jpg	cheval: 0.997

Improving search results

- This sculpture is not found as a result of the current search on the MiC portal for “chien” by Pierre-Jules Mêne (for brevity)



Lévrier tenant un lièvre dans sa gueule by Pierre Jules Mene
© musée de la Vénérie ; Senlis, © Direction des Musées de France, 2009

Sujet scène (chasse :
représe lévrier, lièvre)
nté

Ministère de la Culture

Votre recherche

Recherche avancée

Vos filtres

base: Collections des musées de Fra...

image: oui

mainSearch: chien

domn: sculpture

auteur: MENE Pierre Jules

Affiner par

Auteur

MENE Pierre Jules

MENE Pierre Jules (4)

Domaine

sculpture (4)

Contient une image

oui (4)

non (1)

Est géolocalisée

4 résultats

LISTE CARTE MOSAIQUE

Valet de chien à cheval menant sa harde

groupe relié

MENE Pierre Jules ; France

1869

Paris ; musée du Louvre

Sanglier coiffé par les chiens

statuette

MENE Pierre Jules

2e quart 19e siècle, 2e moitié 19e siècle

Senlis ; musée de la Vénérie

CHIENS AU TERRIER

groupe relié

MENE Pierre Jules ; France

1853

Paris ; musée d'Orsay

Hallali du sanglier


MENE Pierre Jules ; France

1846

Chantilly ; musée Condé




Ranking of the image content

- The thesaurus based labeling mechanism + classifier identified a dog on this image with highest degree of certainty

Image	Labels & Metadata	Prediction
	<p>[0000000001000000000000 000000000000 00000000]</p> <p>chien</p> <p>scène (chasse : lévrier, lièvre)</p> <p>M0810001165</p> <p>C:\Joconde\joconde\0466\m081003_028491_p.jpg</p>	<p>[0000000001000000000000 0000000000000000000000]</p> <p>chien : 0.993</p> <p>cheval : 0.765</p> <p>lion : 0.609</p> <p>oiseau : 0.473</p> <p>mouton : 0.422</p> <p>de profil : 0.235</p> <p>arbre : 0.124</p> <p>cavalier : 0.112</p> <p>fleur : 0.079</p> <p>feuille : 0.036</p>

Ranking of search results

- Running the same query on the Extended Joconde database and sorting by score gives a better result putting the image in the second place

Image	Metadata	Score
	représentation animale (épagneul, debout) M0341003743 C:\Joconde\joconde\0534\m034186_006932_p.jpg	chien: 0.994
	scène (chasse : lévrier, lièvre) M0810001165 C:\Joconde\joconde\0466\m081003_028491_p.jpg	chien: 0.993
	représentation animale (mise à mort, gros gibier : sanglier, chasse à courre, chien) 00000105149 C:\Joconde\joconde\0107\m505206_oa817_p.jpg	chien: 0.990

Conclusions

- **Organizing represented object categories only by Garnier Thesaurus is not sufficient for labeling images**
 - Creating new links between the categories that are semantically and/or visually related but do not exist in Grainier Thesaurus benefits the model training datasets thus creating more accurate classifiers.
- **Multi-label classifiers that recognize more than one object represented on the image can benefit the artwork annotation process**
 - Ranking the detected objects by prediction scores allows detection of “silence” and “noise” in image annotation.
- **Extending the Joconde metadata with DL model generated prediction scores can benefit information retrieval**
 - Using the scores to filter and order search query allows the retrieval of more relevant search results.

Next Steps: MonaLIA 3.0



Château de Bouillon : tête d'escalier by JEAN-HAFFEN Yvonne
© Direction des Musées de France, 1998

- Develop semantic reasoning based on thesaurus and prediction scores
- Augment the training data by performing artistic style transformations of photos for underrepresented categories
- Scale up the multi-label classification to 300 classes depending on image availability
- Explore other state-of-the-art object detection networks to improve on detection performance
- Explore the multi-task learning using the semantic hierarchy
- Explore semantic segmentation with state-of-the-art networks

Thank you

- Acknowledgements:



Dr. Fabien Gandon



Dr. Frédéric Precioso



Francois Reygagne



Ministère de la Culture