AI and Data Science - Machine Learning as Digital Catalyst for Data Curation

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Humanities Data

ROIS-DS Center for Open Data in the Humanities (CODH)

Our team consists of 1 professor, 4 post-docs, and 5 appointed professors.

2016 Pre-center started.

2017 Officially launched.

Member: One director and four project researchers (NII and ISM).

Direction 1: **Innovate humanities research** by computer science and statistical technologies and tools.

Direction 2: **Innovate non-humanities research** by data and questions from humanities.

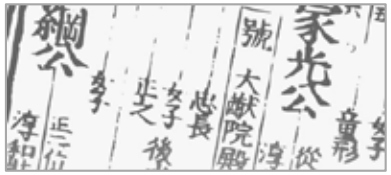
CODH Datasets

http://codh.rois.ac.jp/dataset/

Dataset of Pre-Modern Japanese Text

Kuzushiji Dataset

Dataset of Edo Cooking Recipes



Bukan Complete Collection

Collection of Facial Expressions

Dataset of Historical Administrative Boundaries

How to Access Humanities Data?

Humanities data are mainly textual data, but visual and spatial data requires metadata and annotation to enable **deep access** to content.

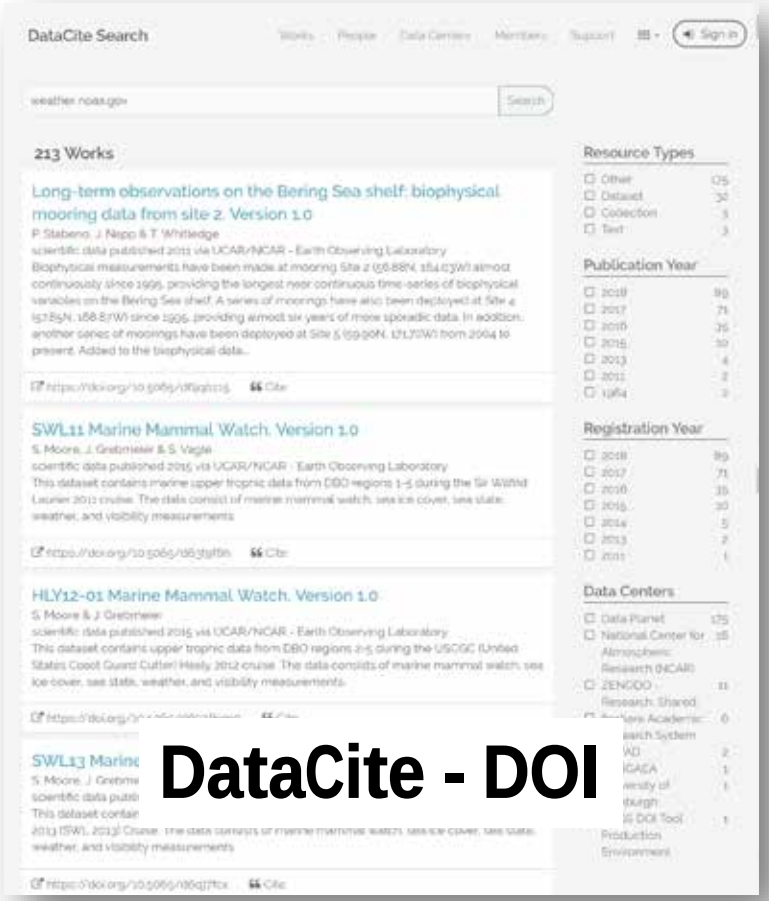
Images

Photographs

Maps

Characters

Knowledge Representation



DataCite - DOI

https://search.datacite.org/

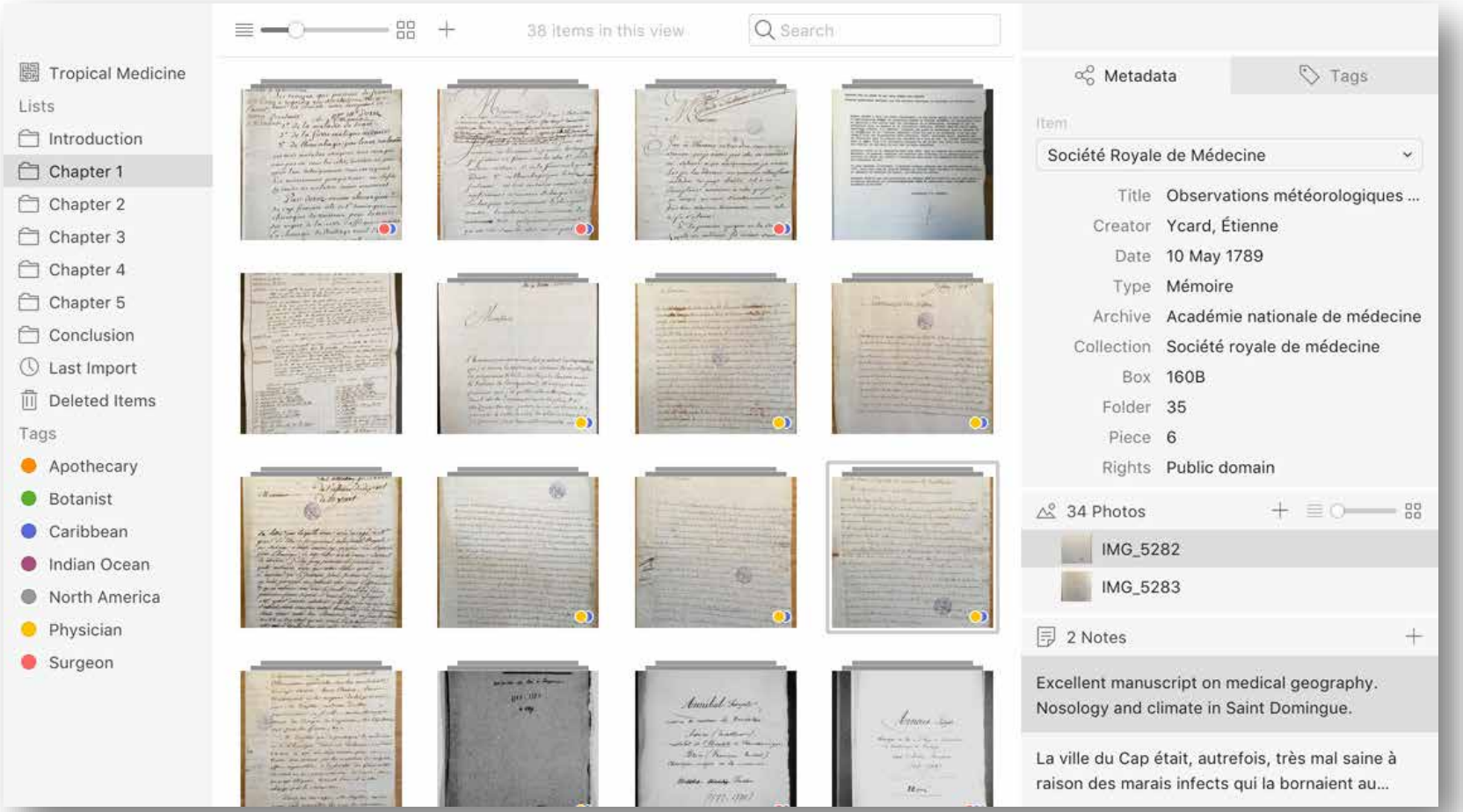
Google Dataset Search – Schema.org

https://toolbox.google.com/datasetsearch

Interoperable metadata and Semantic Web can increase findability.

Manual Image Annotation

https://tropy.org/



Machine Learning (ML)

Credit: David Stanley,
https://www.flickr.com/photos/davidstanleytravel/

Tags

Coconut Grove Beach
Resort Elmina Ghana
landscape shore
seaside outdoor coast
sand

Gray: Human annotated tags,
White: Machine annotated tags.

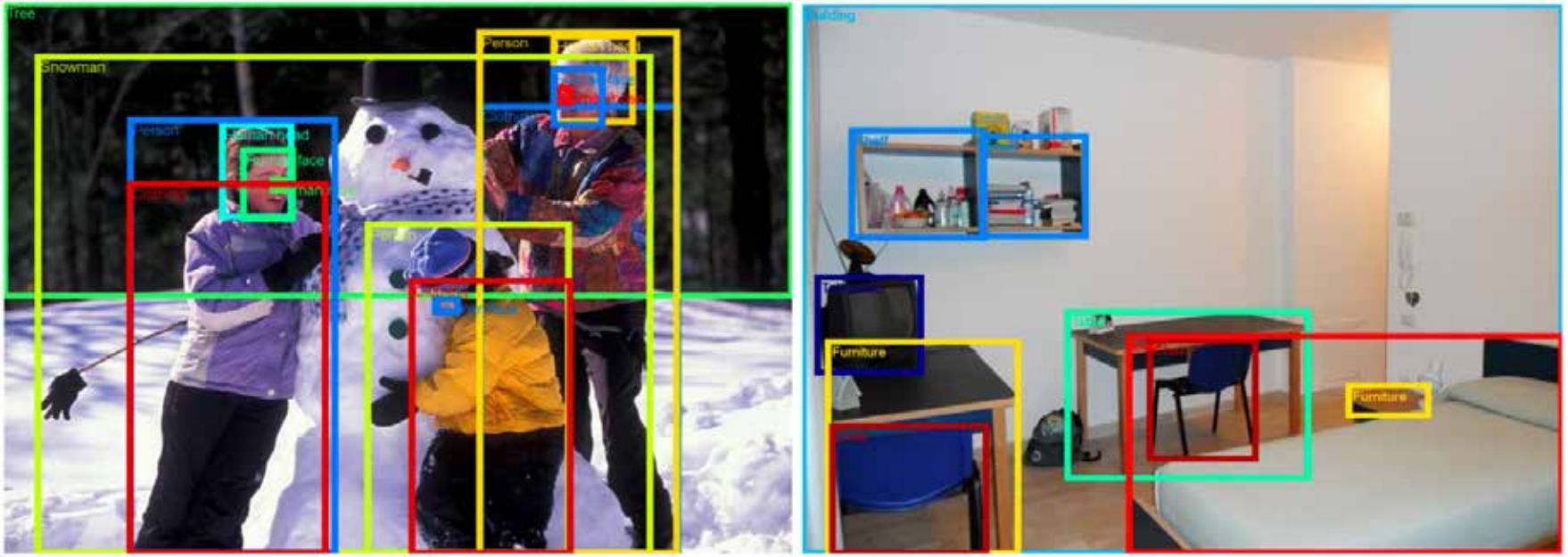
Machine Learning for Photographic Database

Best Practices for AI-assisted Data Curation

1. What could be done by AI, and not by AI?
   Hype and criticism should be corrected.
2. Machine learning: especially effective for learning patterns from image data.
3. Images, especially photographs: selected as the initial target of the work.
4. General numerical datasets: content-based access is still a challenge.

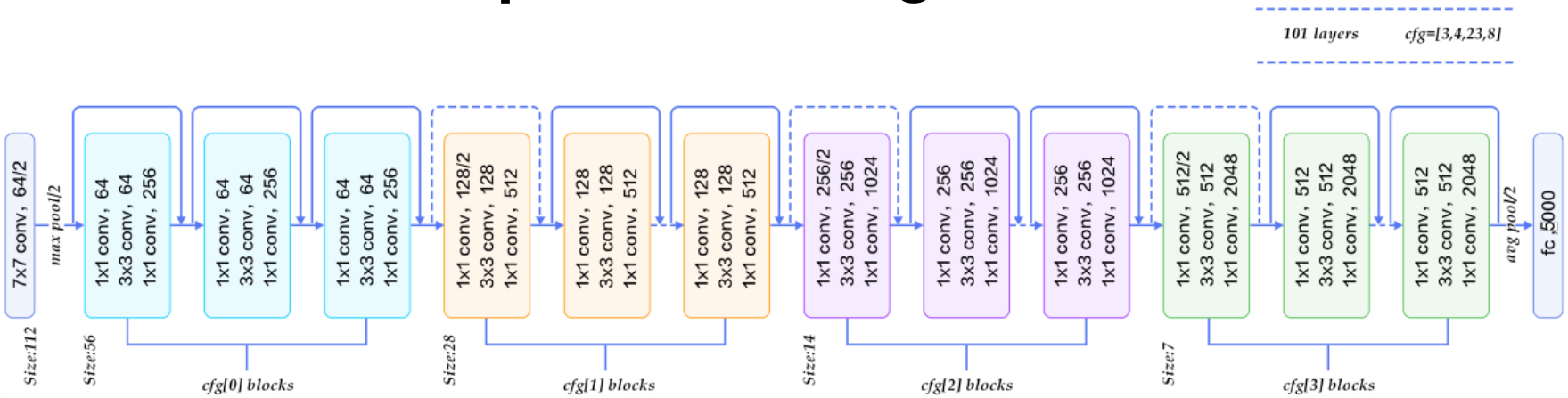
Open Images Dataset V2

https://github.com/openimages/dataset/blob/master/READMEV2.md



Annotated images from the Open Images dataset. Left: FAMILY MAKING A SNOWMAN by mwvchamber. Right: STANZA STUDENTI.S.S. ANNUNZIATA by ersupalermo. Both images used under CC BY 2.0 license.

Deep Learning Model



https://medium.com/@siddharthdas_32104/cnns-architectures-lenet-alexnet-vgg-googlenet-resnet-and-more-666091488df5

1. ResNet 101 classifier learns 5000 tags from 9 million images (Open Images Dataset V2).
2. We used the model already trained on general photographs, not on our dataset.

Case 1: Ethnology Field Work

1. Field work in Ghana, in August 2017.
2. About 3,700 photographs, yet to be released to the public.
3. Collaboration with National Museum of Ethnology (Prof. Yoshida, Prof. Iida and others).

Tag: Person


Person People Child Man
Male Boy Youth Face
Interaction Senior citizen
Person Face Man Facial hair
Head Portrait Senior citizen
Hair Nose Male
Person Official Military officer
Clothing Man Military person
Person Face Glasses Nose
Senior citizen Head Vision care
Portrait Close-up Man
Person Man Glasses Facial hair
Portrait Senior citizen Male
People Conversation Face
Person Baby Child Toddler
Male Boy Skin People Man
Face
Person Baby Child Male Man
Boy Skin Interaction Toddler
Hand
Person Glasses Face Head
Vision care Nose Senior citizen
Portrait Close-up Man
Person Man Male People
Senior citizen Face Head
Facial hair Portrait Hair
Person People Man Hair Male
Hairstyle Facial hair Face Head
Portrait
Person Man People Male
Senior citizen Clothing
Person Male Man People
Child Sitting Boy Portrait
Conversation Senior citizen
1
2
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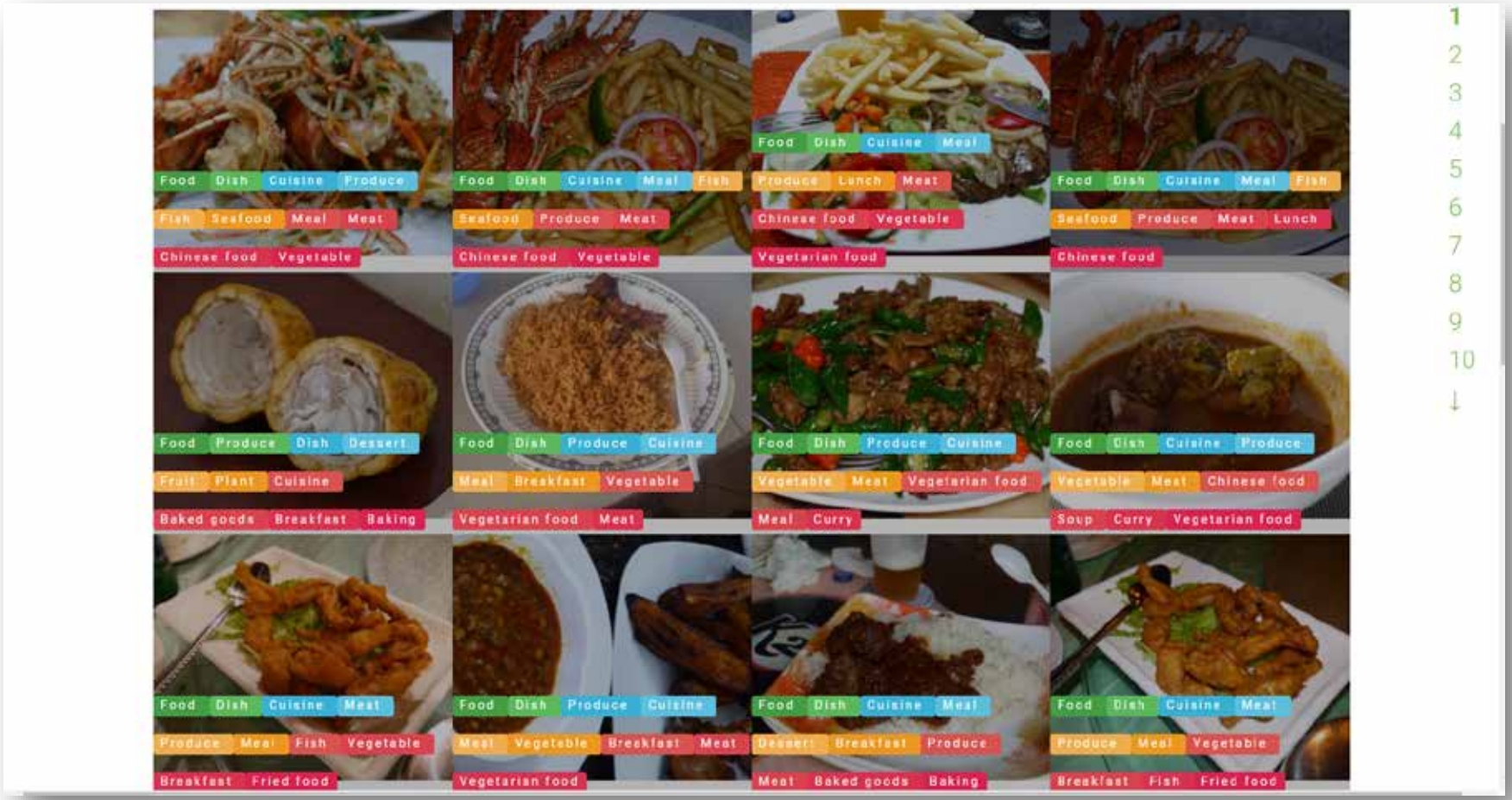
...
30
31

Tag: Food


Food Dish Cuisine Produce
Fish Seafood Meal Meat
Chinese food Vegetable
Food Dish Cuisine Meal Fish
Seafood Produce Meat
Chinese food Vegetable
Food Dish Cuisine Meal
Produce Lunch Meat
Chinese food Vegetable
Vegetarian food
Food Dish Cuisine Meal Fish
Seafood Produce Meat Lunch
Chinese food
Food Produce Dish Dessert
Fruit Plant Cuisine
Baked goods Breakfast Baking
Food Dish Produce Cuisine
Meal Breakfast Vegetable
Vegetarian food Meat
Food Dish Produce Cuisine
Vegetable Meat Vegetarian food
Meal Curry
Food Dish Cuisine Produce
Vegetable Meat Chinese food
Soup Curry Vegetarian food
Food Dish Cuisine Meat
Produce Meal Fish Vegetable
Breakfast Fried food
Food Dish Produce Cuisine
Meal Vegetable Breakfast Meat
Vegetarian food
Food Dish Cuisine Meal
Dessert Breakfast Produce
Meat Baked goods Baking
Food Dish Cuisine Meat
Produce Meal Vegetable
Breakfast Fish Fried food
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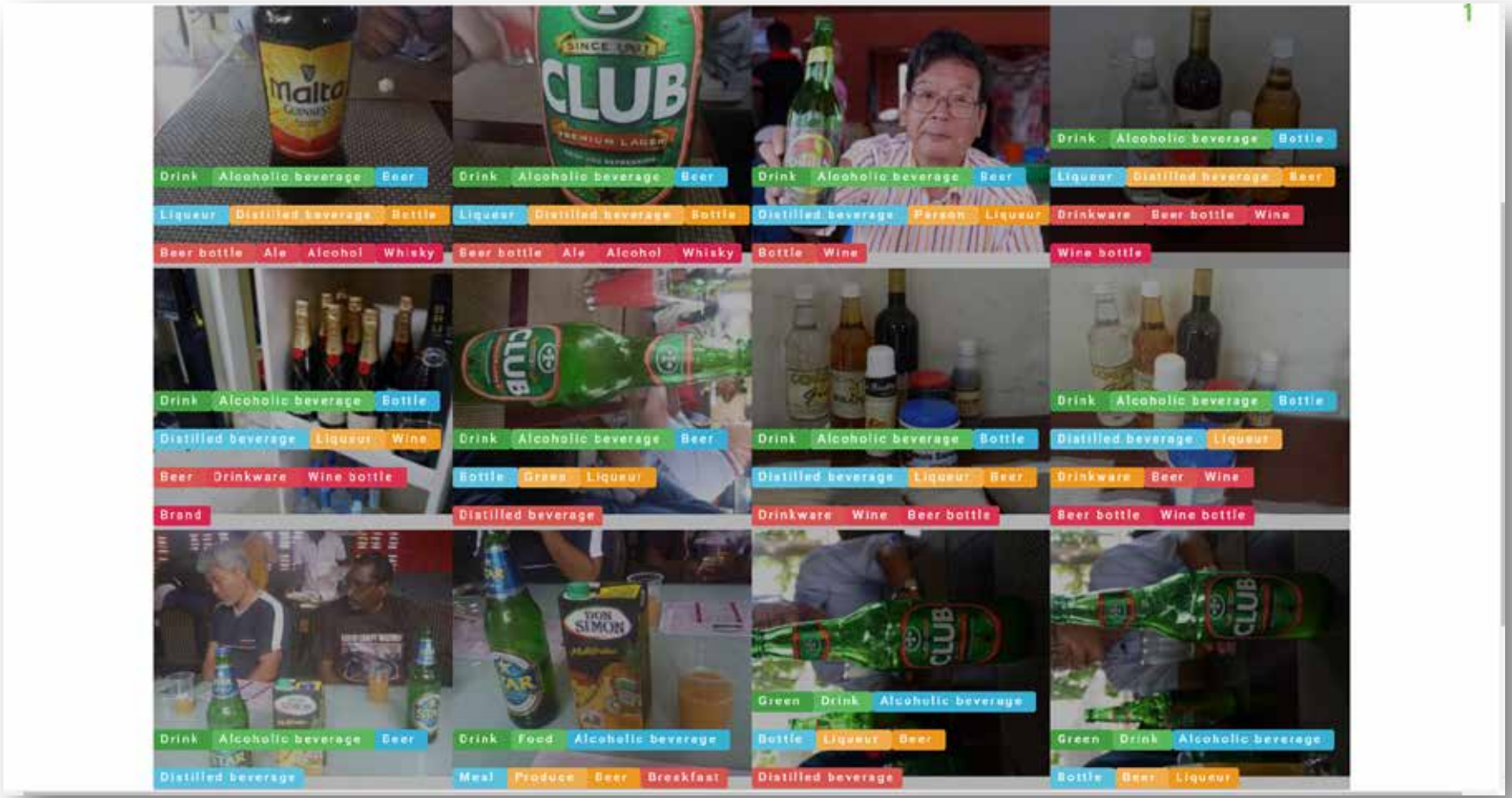
Tag: Beer


Drink Alcoholic beverage Beer
Liqueur Distilled beverage Bottle
Beer bottle Ale Alcohol Whisky
Drink Alcoholic beverage Beer
Liqueur Distilled beverage Bottle
Beer bottle Ale Alcohol Whisky
Drink Alcoholic beverage Beer
Distilled beverage Person Liqueur
Bottle Wine
Drink Alcoholic beverage Bottle
Liqueur Distilled beverage Beer
Drinkware Beer bottle Wine
Wine bottle
Drink Alcoholic beverage Bottle
Distilled beverage Liqueur Wine
Beer Drinkware Wine bottle
Brand
Drink Alcoholic beverage Beer
Bottle Green Liqueur
Distilled beverage
Drink Alcoholic beverage Bottle
Distilled beverage Liqueur Beer
Drinkware Wine Beer bottle
Drink Alcoholic beverage Bottle
Distilled beverage Liqueur
Drinkware Beer Wine
Beer bottle Wine bottle
Drink Alcoholic beverage Beer
Distilled beverage
Drink Food Alcoholic beverage
Meal Produce Beer Breakfast
Green Drink Alcoholic beverage
Bottle Liqueur Beer
Distilled beverage
Green Drink Alcoholic beverage
Bottle Beer Liqueur

Tag: Art


Art Mural Graffiti Street art
Urban area Wall Street
Advertising Road Poster
Art Textile Wall Drawing
Design Mural Pattern Painting
Art Textile Pattern Quilting
Quilt Bed sheet Design
Sculpture Statue Art Green
Monument Carving Head
Stone carving Ancient history
Close-up
Art Mural Graffiti Street art
Illustration Modern art Painting
Poster
Art Mural Graffiti Wall
Advertising Street art Modern art
Painting
Textile Art Yellow Pattern
Design Furniture Bed sheet
Flooring Quilting Quilt
Art Painting Mural Modern art
Drawing Wall
Blue Wall Art Graffiti Mural
Urban area Window Street art
Iron Street
Art Painting Modern art
Picture frame Drawing Sketch
Portrait Person
Art Mural Painting Textile
Art Wall Font Calligraphy
Drawing Handwriting Number
Text Sketch Graffiti
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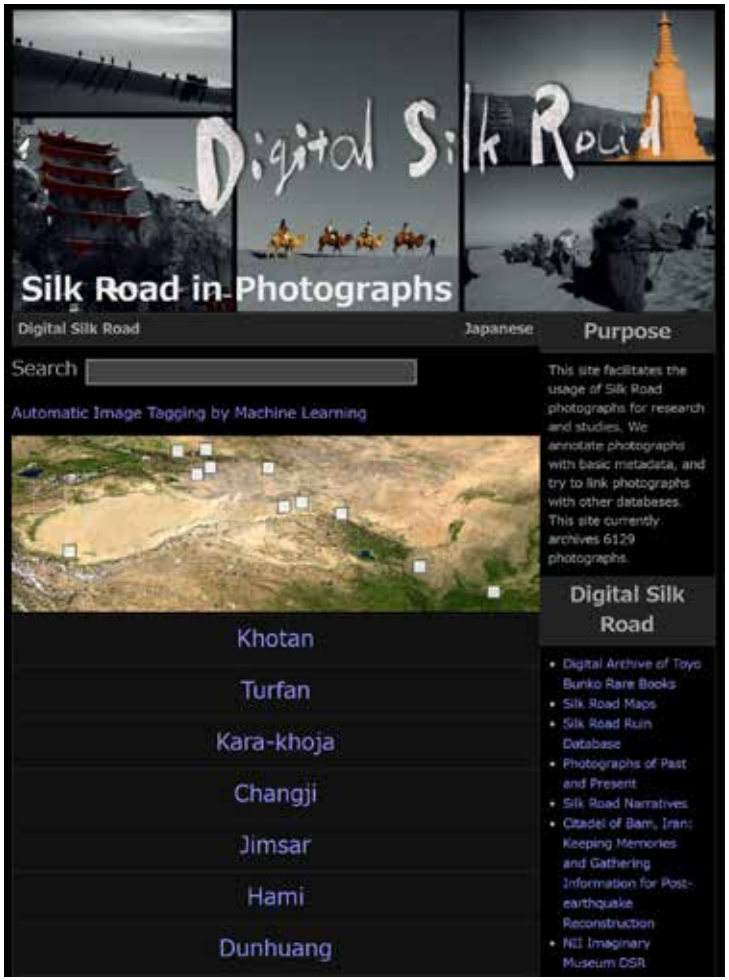
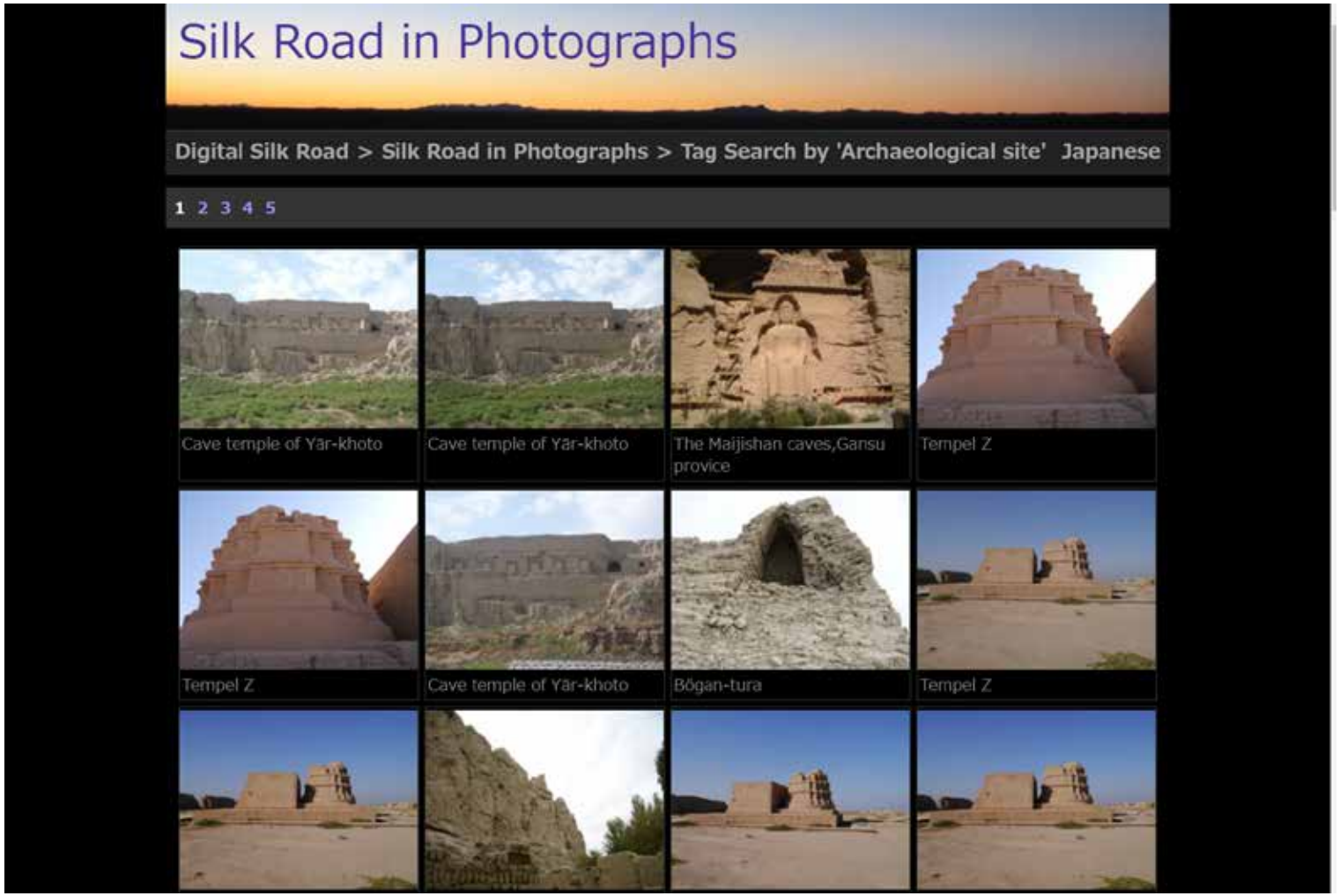
Case 2: Archaeology Field Work

http://dsr.nii.ac.jp/photograph/



1. Photographs of the Silk Road, mainly about old ruins.
2. 6,129 photographs across long time span.
3. Many photographs were taken by Dr. Nishimura in Toyo University.

Tag: Archaeological Site



Tag: Snow


Silk Road in Photographs
Digital Silk Road > Silk Road in Photographs > Tag Search by 'Snow'
Japanese
1 2 3 4
Ruined town of Nanhu (Ancient city of Shou'chang)
Ruined town of Nanhu (Ancient city of Shou'chang)
Ruined town of Nanhu (Ancient city of Shou'chang)
Ruined town of Nanhu (Ancient city of Shou'chang)
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Ruined town of Nanhu (Ancient city of Shou'chang)
Ruined town of Nanhu (Ancient city of Shou'chang)
Ruined town of Nanhu (Ancient city of Shou'chang)

Tag: Wood


Silk Road in Photographs
Digital Silk Road > Silk Road in Photographs > Tag Search by 'Wood'
Japanese
1 2 3 4
Khohmari caves
Ruined buddhist shirines, Ara-tam
Tempel Z
Tempel Z
Tempel Z
Tempel κ
Tempel Z
Tamguluk-tāsh

Different Responses from Users

Ethnology Field Work	Archaeology Field Work
Image tagging has great potential for grouping photographs by theme.	Grouping by machine-generated tags is less useful than grouping by entity names.
Even if the tag is not correct, it gives some hints about the content.	Some tags are simply wrong due to different training images and domains.

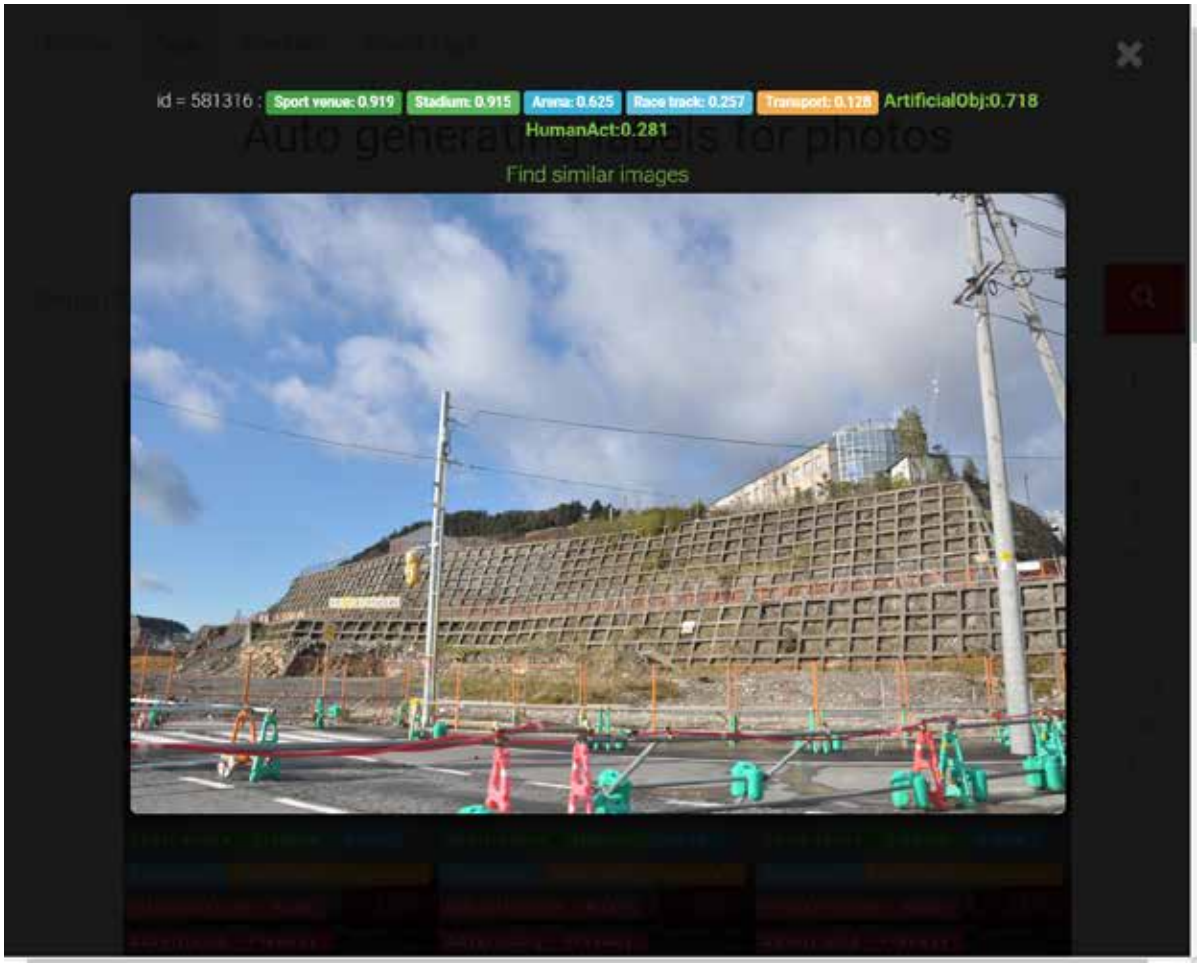
Why Different Reponses?

General Noun Metadata	Proper Noun Metadata
Ethnology photographs are so diverse that tags of general nouns are effective for grouping.	Archaeology photographs are usually taken with intentions.
It motivates experts to describe deeper metadata.	Entity names are difficult to identify by machine learning.

Case 3: Post-Disaster Survey

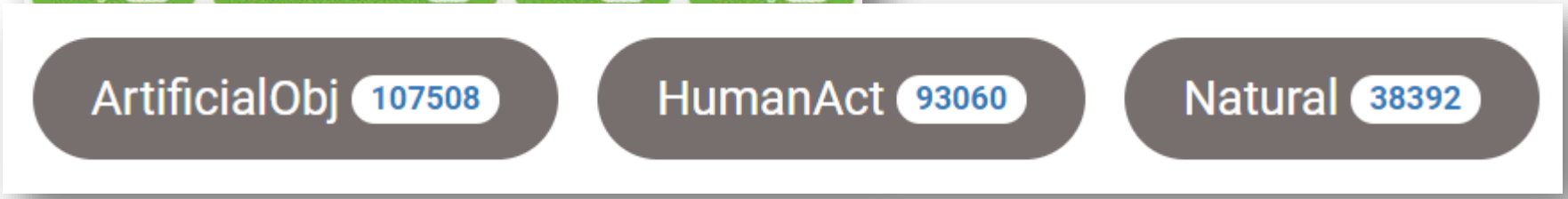
1. Photographs of East Japan Earthquake 2011 and Kumamoto Earthquake 2016.
2. More than 10,000 photographs, yet to be released to the public.
3. Collaboration with National Research Institute for Earth Science and Disaster Resilience (NIED).

Serendipity
Tag: Stadium



Semantic Grouping of Low-Level Tags

Domain experts need higher-level semantic grouping of low-level tags.



Case 4: Historical Photographs

http://codh.rois.ac.jp/north-china-railway/

1. Photographs of North China Railway, a company existed around 1940.
2. More than 35,000 photographs will be released in Feb. 2019.
3. Collaboration with Kyoto University.

Image Tagging

Road, Street, Black-and-white, Monochrome photography, Monochrome, Infrastructure, Transport, Lane, Vehicle, Photograph

Image Colorization

Image Tagging after Colorization

Road, Street, Infrastructure, Town, Transport, Photograph, Urban area, Vehicle, Lane, Pedestrian

Lessons from Two Collections

1. Two photographic collections are too large for humans to annotate one by one.
2. Automatic tagging may be useful as the initial step for improving findability.
3. Statistical research questions, such as thematic distribution may be answered.
4. Other methods can improve findability, such as colorization and object detection.

The Value of Data and FAIR Principle

The Value of Data

1. Intrinsic Value

Raw data

scientists / scholars

2. Basic Value

Organized data

(data) librarians

3. Added Value

Integrated data

(data) curators

4. Persistent Value

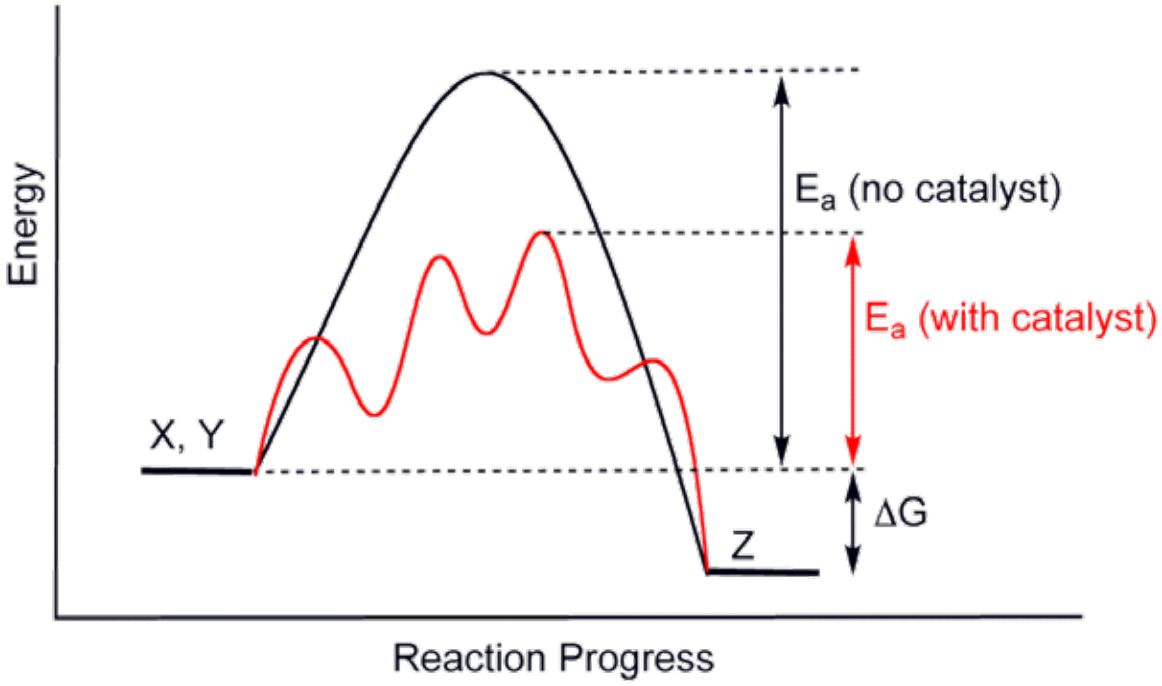
Preserved data

(data) archivists

Machine Learning for Increasing the Value of Data

1. Basic value and added value need high quality metadata for higher value.
2. FAIR (Findable, Accessible, Interoperable, Reusable) principle asks for good metadata.
3. Humans procrastinate in adding metadata, hence the workflow does not start.
4. Use machines to quickly reach **a state which is better than nothing.**

Digital Catalyst



https://commons.wikimedia.org/wiki/File:CatalysisScheme.png

To reach a state of curated data, we need to go beyond the high energy barrier.

Machine learning as digital catalyst reduces the barrier, requiring less human motivation to pass the barrier.

Human-Machine Collaborative Workflow

1. **Machines** can automatically add general noun tags for coarse grouping.
2. **Humans** can manually add proper noun tags for fine meaning as metadata.
3. **Domain experts** can add high-level metadata and semantic grouping.
4. **ML models** can use added metadata as new training data to improve performance.

Conclusion

1. Machine learning, e.g. image tagging, is beneficial for improving findability.
2. General nouns are useful for some apps; other apps require higher level metadata.
3. Better findability (curation) increases the basic value and added value of data.
4. Digital catalyst is a concept of machine-assisted data curation to motivate humans.

Acknowledgment and Links

Photograph collections were provided from the following collaborators:

Dr. Taku Iida in National Museum of Ethnology

Dr. Yoko Nishimura in Toyo University

Ms. Hinako Suzuki in National Research Institute for Earth Science and Disaster Resilience

Dr. Toshihiko Kishi and his colleagues in Kyoto University.

A part of the machine learning workflow was developed by:

Hoàng Văn, Hà (Vietnam National University, HCMC) during NII internship.

- Center for Open Data in the Humanities
  - http://codh.rois.ac.jp/
- Open Science
  - http://agora.ex.nii.ac.jp/~kitamoto/research/open-science/
- Researchmap
  - http://researchmap.jp/kitamoto/