



Workflow pro automatické rozpoznávání archeologických nálezů pomocí umělé inteligence (AI)

Workflow for Automated Archaeological Artifact Recognition using AI

Petr Pajdla & Ronald Harasim

Motivation and objectives

- Manual processing of archaeological archives is a tedious, time consuming, and challenging task prone to human errors and inconsistencies...
 - This makes it a prime candidate for automation.
 - Archives of ARUP & ARUB hold around:
 - ~140k documents, ie. ~1.5m pages
 - 500k of various photographs
 - Improve/enhance metadata in the  Archaeological map of the Czech Republic and  ARIADNE



Archaeological map of
the Czech Republic



(Images: Archive of the Institute of Archaeology, Czech Acad. Sci, Brno)

Advancing Frontier Research in the Arts and Humanities

- Horizon EU project
- Focus on workflows and demonstrators

“Facilitating access to digital research infrastructures and advancing frontier knowledge in the arts and humanities — across disciplines, languages and media.”

Transnational Access – Travel Grants

- Current call for applicants is open until 31 May, 2025!
<http://atrium-research.eu>



Workflows overview

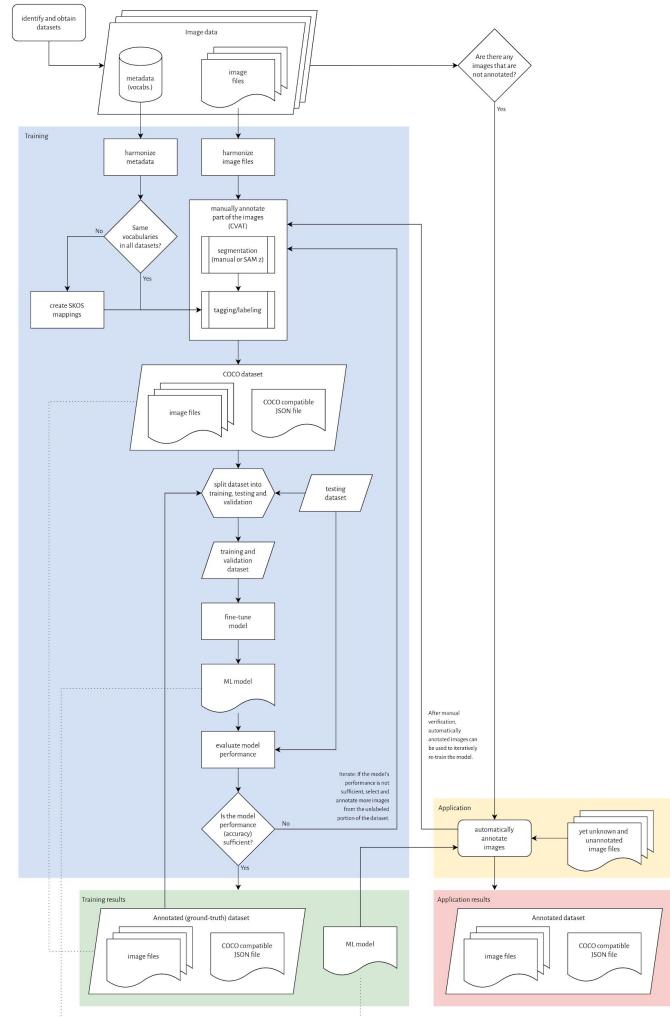
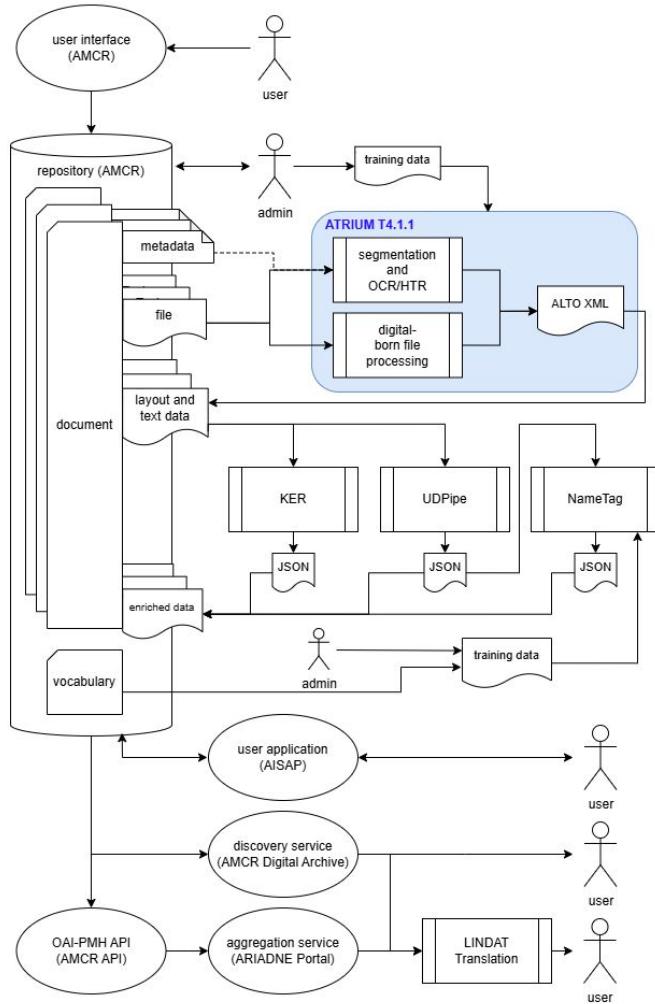
- Text-based workflow

Model for page classification

<https://github.com/ufal/atrium-page-classification>

(details in the poster by Dana Křivánková and Kate Lutsai)

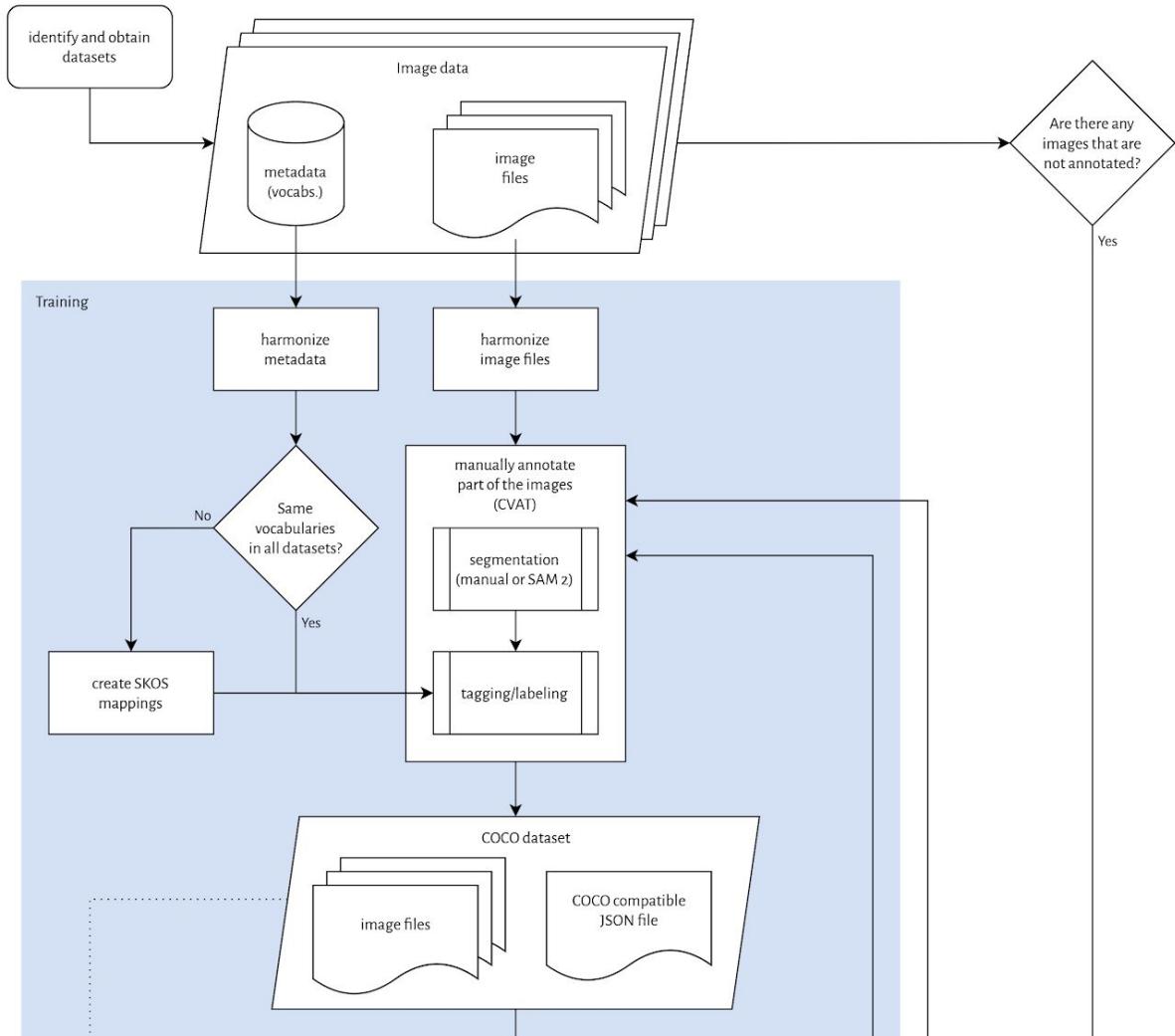
- Image-based workflow



Automatic image annotation workflow

Goals:

- **Automatic annotation** of images (photographs) with terms from controlled vocabularies
- Enhanced **findability**, enriched **metadata**
- Object **extraction** etc.



(1) Consider the goal and use-case



"This archaeological excavation reveals an ancient burial with human skeletal remains surrounded by stone artifacts and pottery fragments. Most notably, a prominent iron sword lies centrally alongside the body, suggesting a warrior or high-status burial. A stone headrest or marker is visible at the far end of the rectangular pit."

(Claude 3.7 Sonnet)

- **Viewing using LLMs**
 - Description in natural language followed by vocabulary matching
 - Optionally output in machine-readable format (eg. JSON)
 - Expensive in terms of computing resources and/or price
- **Traditional computer vision models**
 - Versatile and lightweight models
 - "Garbage in, garbage out", does not hallucinate
 - Expensive in terms of time/workforce invested in the dataset creation

(Image DOI: 10.60585/M-FT-110736000)

(2) Gather and harmonize image data

Image data come in all shapes and sizes...

- Transform to a common bitmap format (JPEG)
 - TIFFs might be challenging (transparency, multi-page files etc.)
- 3-channel input expected (RGB)
- Further optimization depends on the model selection...

```
def process_tiff_image(img: Image.Image) -> Image.Image:  
    """Process TIFF images, handling multiple frames and bit depths."""  
    # Count frames  
    try:  
        n_frames = 0  
        while True:  
            img.seek(n_frames)  
            n_frames += 1  
    except EOFError:  
        pass  
  
    # Return single-frame TIFF as is  
    if n_frames <= 1:  
        img.seek(0)  
        return img  
  
    # Find best frame (with most content)  
    best_frame, max_std = 0, 0  
    for i in range(n_frames):  
        img.seek(i)  
        std_dev = sum(abs(px - 128) for px in img.convert('RGB').convert('L').getdata()) / (img.width *  
            img.height)  
        if std_dev > max_std:  
            max_std, best_frame = std_dev, i  
  
    img.seek(best_frame)  
    return img  
  
def convert_image_mode(img: Image.Image) -> Image.Image:  
    """Convert image to appropriate mode for JPEG saving."""  
    original_mode = img.mode  
  
    # Convert based on mode  
    if original_mode in ('I;16', 'I'):  
        img = img.point(lambda i: i * (255.0 / 65535.0)).convert('L')  
    elif original_mode == 'F':  
        img = img.convert('RGB')  
  
    if original_mode == 'P' and 'transparency' in img.info:  
        img = img.convert('RGB')  
        img.putalpha(255)  
    else:  
        img = img.convert('RGB')  
    return img
```

(3) Align controlled vocabulary terms

- skos:mappingRelation
 - skos:closeMatch
 - skos:**exactMatch**
 - skos:broadMatch
 - skos:narrowMatch
 - skos:relatedMatch

Datasets /1

Photographs of finds

- AMCR-PAS
 - >7.5k finds, ~10k photographs
- “Lovec pokladů” (“Treasure hunter”)
 - >300k finds
 - photographs by metal detectorists
 - quality varies greatly
- Portable Antiquities Scheme
 - >750k finds (with images)
 - high quality of images
- Montelius dataset
 - includes drawings and images scanned from published resources



(Images: AMCR-PAS, Lovec pokladů, Portable Antiquities Scheme)

Datasets /2

Photographs of fieldwork

- ARUP digital photographs of fieldwork collection
 - >60k photographs
- ARUP & ARUB archival photographs
 - ~300k photographs
 - various scenes, fieldwork, people, finds, sites etc.
 - mostly b/w photographs



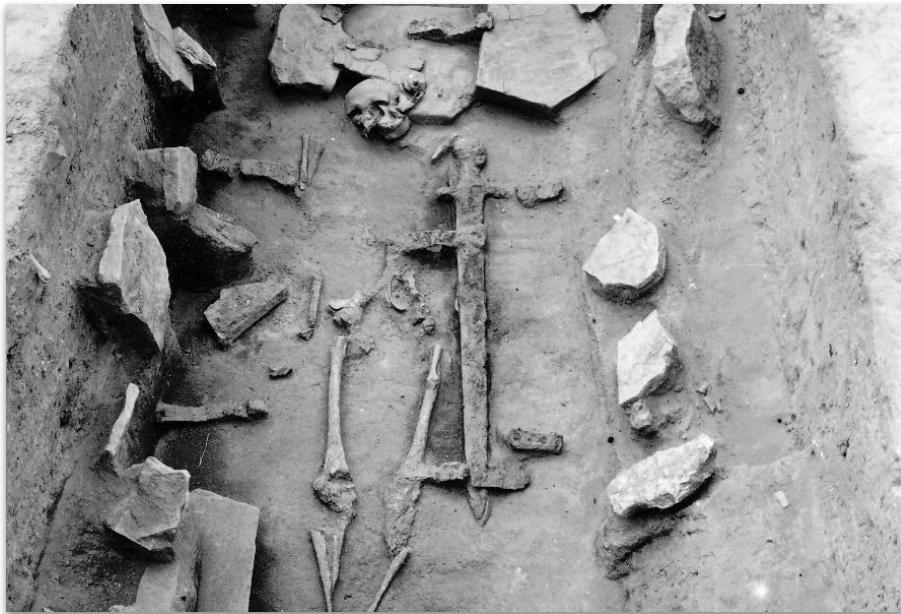
(Images: Digital Archive of the Archaeological Map of the Czech Republic)



(4) Annotate images

- Various **annotation platforms...**
 - CVAT (Computer Vision Annotation Tool)
<https://www.cvcat.ai/>
 - VIA (VGG Image Annotator)
<https://www.robots.ox.ac.uk/~vgg/software/via/>
- BBoxes vs **segmentation**
- Segment Anything Model (**SAM2**)
 - Semantic segmentation
 - <https://ai.meta.com/sam2/>
- **COCO compatible JSON**
- Annotation of **AMCR-PAS dataset**
 - **9764** images, **7303** annotated (~65 %)
 - **7426** objects (annotations)
 - speed: **~50** objects per hour

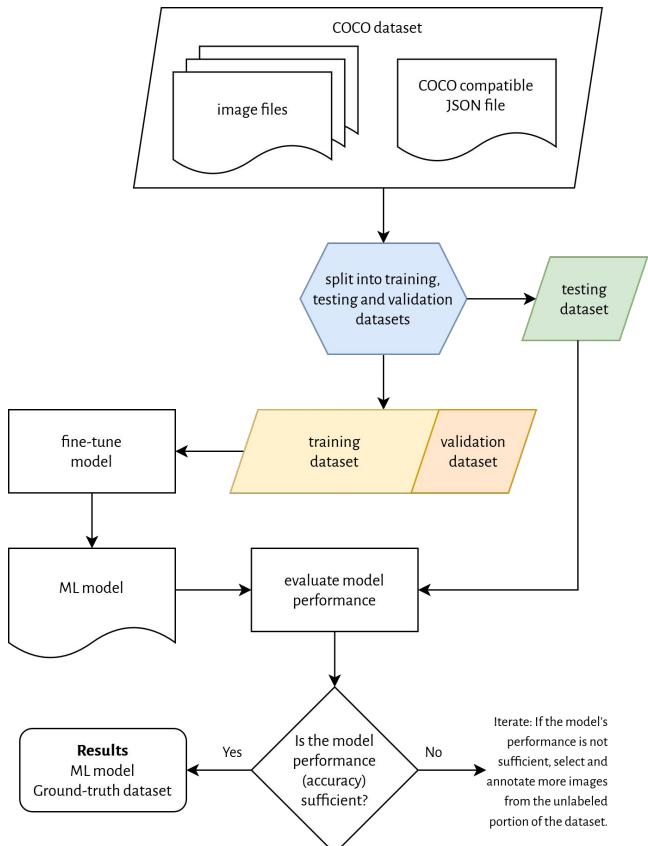
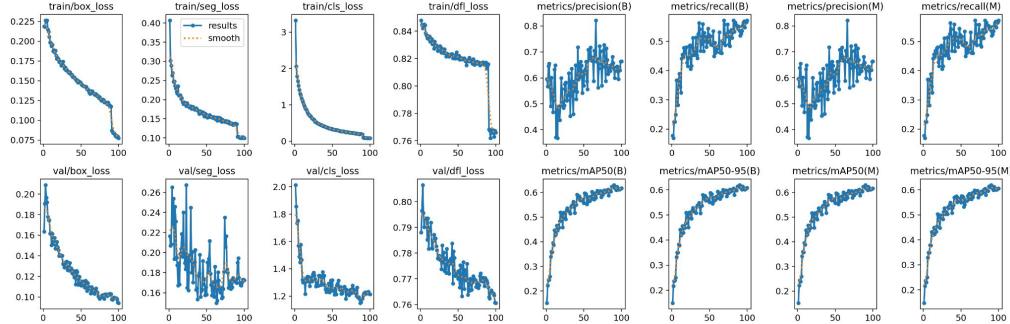
```
"annotations": [  
    {  
        "id": 1,  
        "image_id": 1,  
        "category_id": 1,  
        "segmentation": [  
            [  
                555.0,  
                682.0,  
                548.0,  
                683.0,  
                529.0,  
                697.0,  
                518.0,  
                701.0,  
                492.0,  
                717.0,  
                429.0,  
                766.0,  
                382.0,  
                857.0,  
                361.0,  
                910.0,  
                361.0,  
                931.0,  
                354.0,  
                949.0,  
                342.0,  
                1026.0,  
                350.0,  
                1038.0,  
                383.0,  
                1057.0,  
                416.0,  
                1059.0,  
                431.0,  
                1065.0,  
                438.0,  
                1063.0,  
                462.0,  
                1063.0,  
                512.0,  
                1046.0,  
                553.0,  
                1046.0,  
                586.0,  
                1041.0,  
                555.0  
            ]  
        ]  
    }  
]
```



(Image DOIs
10.60585/M-FT-110736000 and
10.71928/M-202300087-N00394)

(5) Re-train/fine-tune the model

- Split into **training**, **validation** and **testing** datasets
 - **Imbalanced** dataset – proportional representation of classes...
- **YOLO v11 seg.**, 100 epochs, PyTorch
 - Best results with **340x340px** resolution
 - Detection (BBox) mAP_{50–95} ≈ 0.61
 - Segmentation (mask) mAP_{50–95} ≈ 0.61



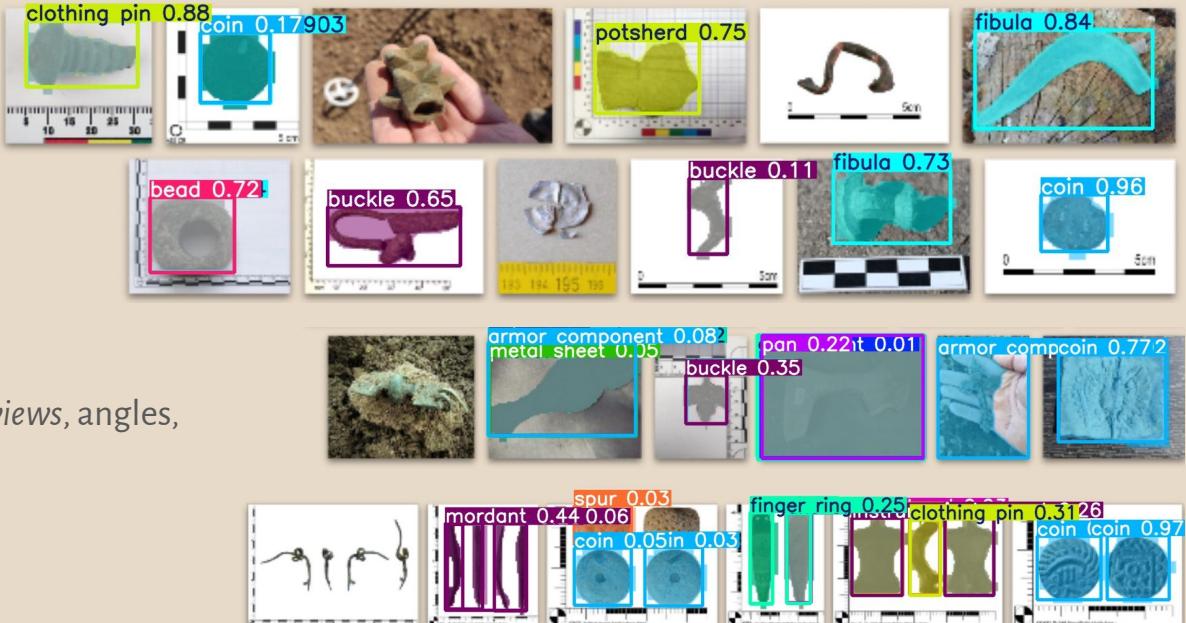
(6a) Apply the ML model

Apply the model, verify the results, iterate...

- First good version of the model helps with further annotations...
- Ground-truth dataset grows

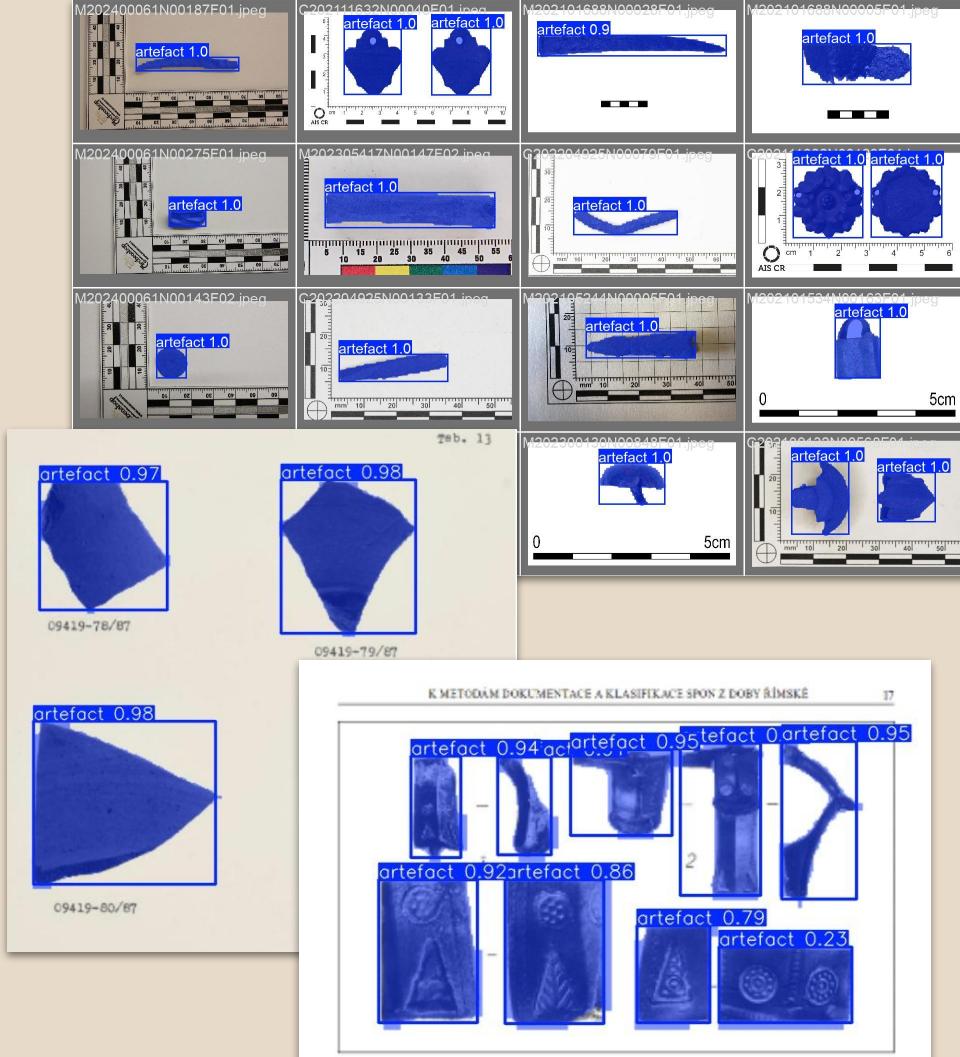
TODOs:

- Cope with **imbalanced dataset**
- Cope with **variability** of different views, angles, sizes etc.
- Enlarge *ground-truth* dataset...



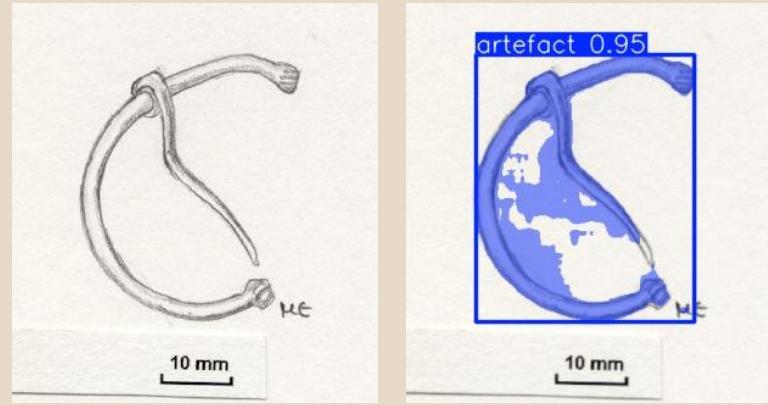
(6b) Artifact Database

1. **Input:** Photographs containing artifacts.
2. **Detection & Segmentation:** A pre-trained model automatically finds and precisely outlines (segments) artifacts in the photographs.
3. **Artifact Extraction:** Identified artifacts are "cut out" from the photographs as separate images.
4. **Vectorization (Visual Transformer):** Each extracted artifact is processed by a Visual Transformer, which creates a unique semantic vector (a numerical "fingerprint" of the artifact).
5. **Database Storage:** All vectors representing the artifacts are stored in a specialized vector database.



(6b) Searching for similar Artifacts

1. **Input (Query):** A new image of an artifact for which we want to find similar ones.
2. **Query Processing:**
 - a. The input image undergoes the same **detection, segmentation, and extraction** process as during database creation.
 - b. The extracted artifact from the query is then converted into a **vector** using the same Visual Transformer.
3. **Database Comparison:** The query artifact's vector is compared against all vectors in the artifact database.
4. **Output:** Display of artifacts from the database whose vectors are mathematically most similar to the query vector.



Sidenote: LLM Fine-Tuning & Deployment

Models used:

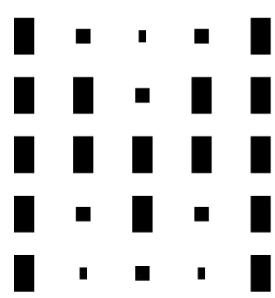
- Qwen 2.5 VL
- Gemma 3 27B

Our Local Setup:

- **Hardware:** In-house NVIDIA RTX 4090 GPUs (24GB VRAM)
- **Fine-tuning Engine:** Unsloth library (for efficient training)
- **Serving Framework:** Ollama (for local model utilization)

Focus: Tailoring advanced LLMs for our specific applications using our own infrastructure.





MAiA

Managing
Artificial Intelligence
in Archaeology

'MAIA is here to investigate Artificial Intelligence (AI) applications within archaeology.'

- <https://www.maiacost.eu/>
- COST Action CA23141
- > 200 members...
- At least 3-4(?) **surveys** planned...
- Training **school** on **data management for AI applications** at **ADS** (York, 2nd week of September?)

Working groups:

1. State of the Art: AI and Archaeology
2. Digital Comparative Collections and AI Training Data for Archaeology
3. AI and Archaeological Research
4. Dissemination and Communication



Thank you for listening!

For more information, please visit <https://www.atrium-research.eu/>



Funded by
the European Union

Petr Pajdla
pajdla@arub.cz

Czech Academy of Sciences, Institute of Archaeology, Brno

Ronald Harasim
harasim@arub.cz

Czech Academy of Sciences, Institute of Archaeology, Brno

...and special thanks to the ARUB & ARUP annotation team!

Kristína Rašlová, Zuzana Kopáčová, Eva Buchtová, Tomáš Chlup
David Spáčil, David Novák, Olga Lečbychová