Towards human-aided document processing for Optical Music Recognition

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DDMAL DISTRIBUTED DIGITAL MUSIC ARCHIVES & LIBRARIES LAB
Schulich School of Music École de musique Schulich
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CIRMMT Centre for Interdisciplinary Research in Music Media and Technology

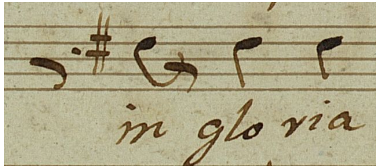
Introduction

- Digital encoding of music enables a wide range of applications
- Many written music remains only in physical format
- Typesetting music represents a costly endeavor
- Optical Music Recognition can be seen as the key to increasing the number of available encoded music sources

Introduction

- Optical Music Recognition (OMR) is the field that studies how to make computers capable of reading music
- Difficulties of OMR
  - Music notation is complex
  - Music manuscripts are highly heterogeneous
    - Document conditions
    - Sheet organization
    - Notational systems

Introduction

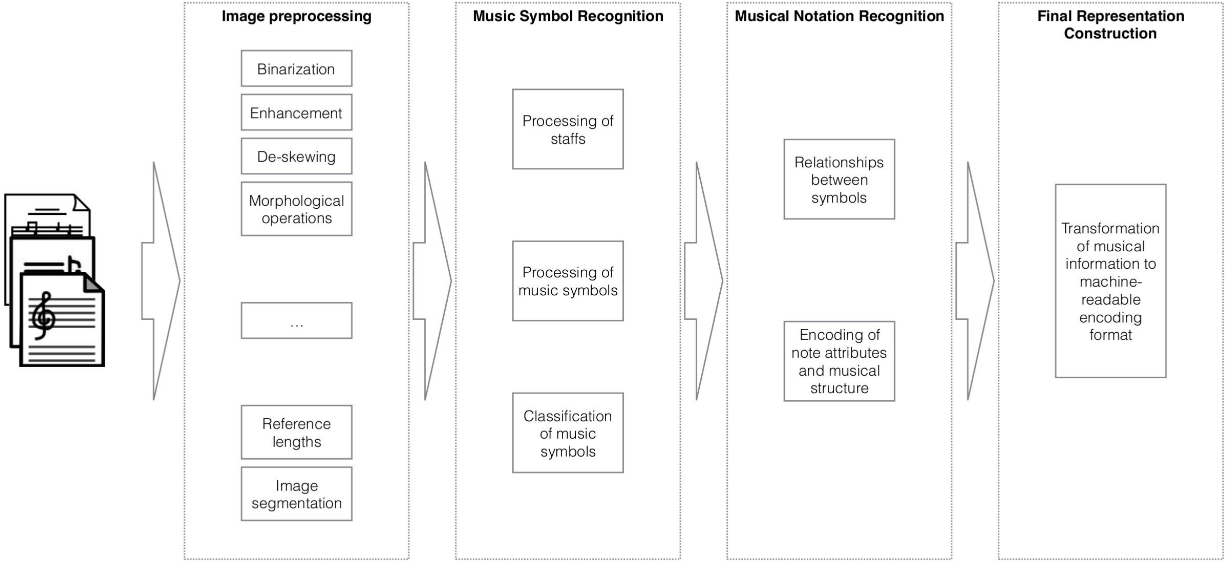


Introduction

- The “universal OMR” may be out of reach
- General OMR workflow
  - Document processing
  - Music symbol recognition
  - Notation assembly
  - Encoding

Framework

Optical Music Recognition workflow



Framework

Optical Music Recognition workflow

- Sequential stages: errors are propagated
- Each stage should be checked before going on
- It is necessary to involve the user in the process
  - Human-aided Optical Music Recognition workflow

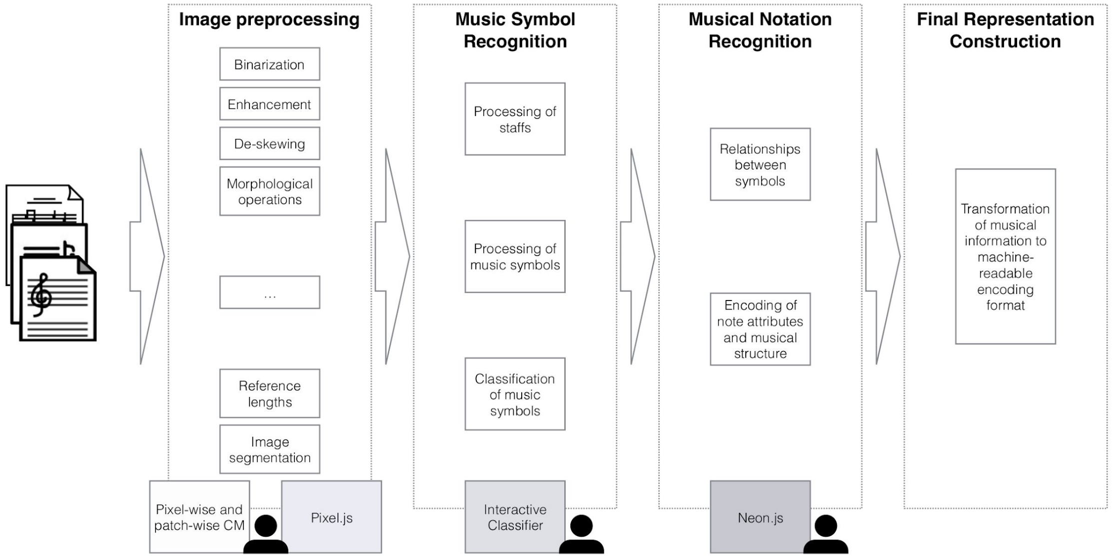
Introduction

Human-aided Optical Music Recognition workflow

- Involve the user in the process to guide the computer
- User is necessary: take the most out of it
- The OMR stages should not be fixed, but allow adaptation

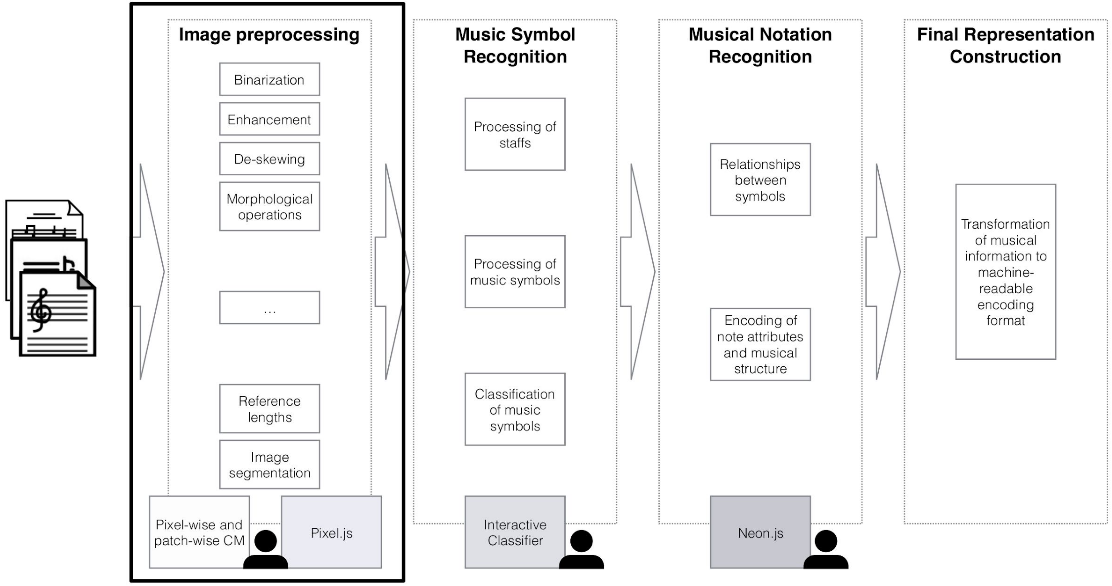
Framework

Human-aided Optical Music Recognition workflow



Framework

Human-aided Optical Music Recognition workflow



Framework

Document processing

- Separate the content of the document into its constituent layers

Framework

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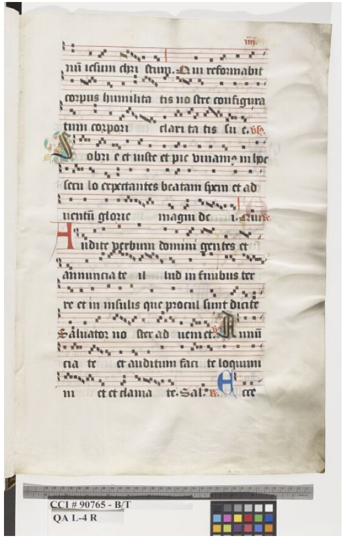
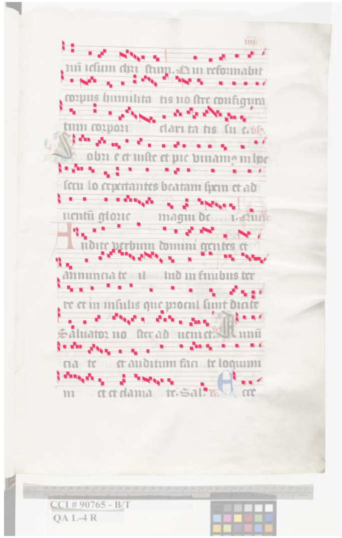
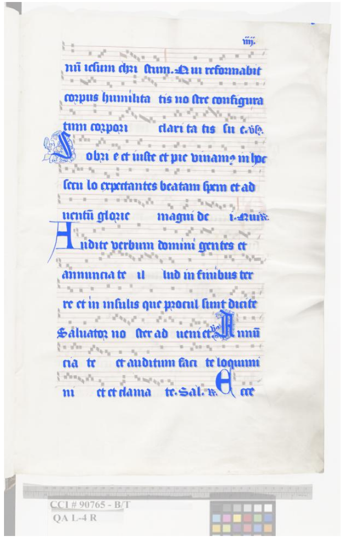
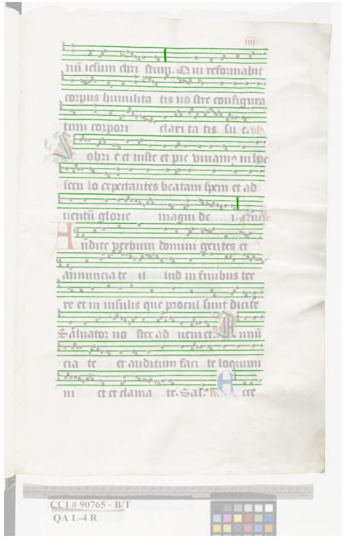

Human-aided music document analysis

Core processes

- Machine Analysis
- Human Teaching

Human-aided document analysis

Machine Analysis

- Avoid hand-crafted procedures that exploit specific characteristics
- We need models that learn to do the task
- This naturally leads to machine learning techniques
  - Ground-truth data is necessary for the models to be trained

Human-aided document analysis

Machine Analysis

- Our workflow requires detection at pixel level
- Pixelwise Classification Method (CM) with Convolutional Neural Networks
  - The surrounding region of each pixel contains enough discriminative information
  - The network is trained from a large number of examples for each category
  - It learns the regularities in these examples and creates a model out of the data
  - Once a model is trained, it is used to classify new examples

Human-aided document analysis

Machine Analysis: Convolutional Neural Networks

- Convolutional Neural Networks represent the state of the art in computer vision and image processing tasks
- Hierarchy of filters (convolutions) that process an image to predict a label
- Filters are not fixed but learned through a training process
- Feature extraction is not necessary

Human-aided document analysis

Machine Analysis

- Pixelwise Classification Method (CM) with Convolutional Neural Networks

Human-aided document analysis

Machine Analysis

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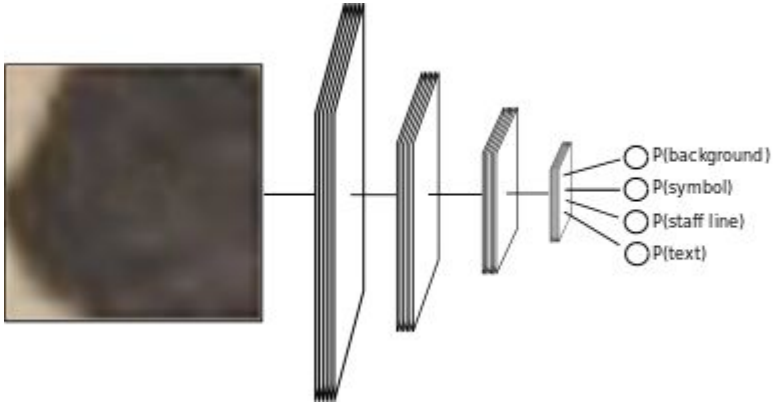

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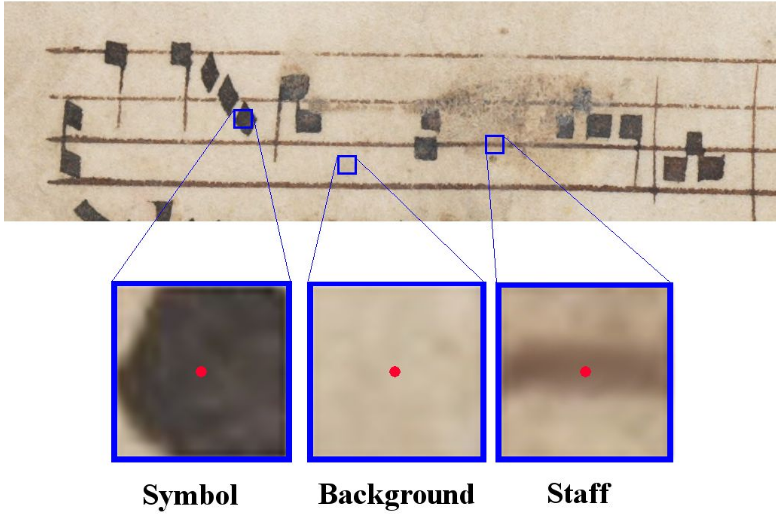
Machine Analysis

- Pixelwise Classification Method (CM) with Convolutional Neural Networks



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Machine Analysis

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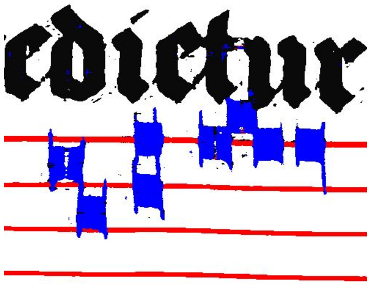

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Machine Analysis

- Pixelwise CM
    - Advantages
        - Learning-driven model
        - Good performance
        - Learning from limited ground-truth data
    - Disadvantages
        - High temporal cost

Human-aided document analysis

Machine Analysis

- The temporal cost of the pixelwise CM represents a troublesome bottleneck
- Patchwise CM with Auto-Encoders
  - Replace the CNN classifier by class-wise (Convolutional) Auto-Encoders
  - Filters learn an image-to-image prediction
  - Process a complete sub-image (patch) in a single step

Human-aided document analysis

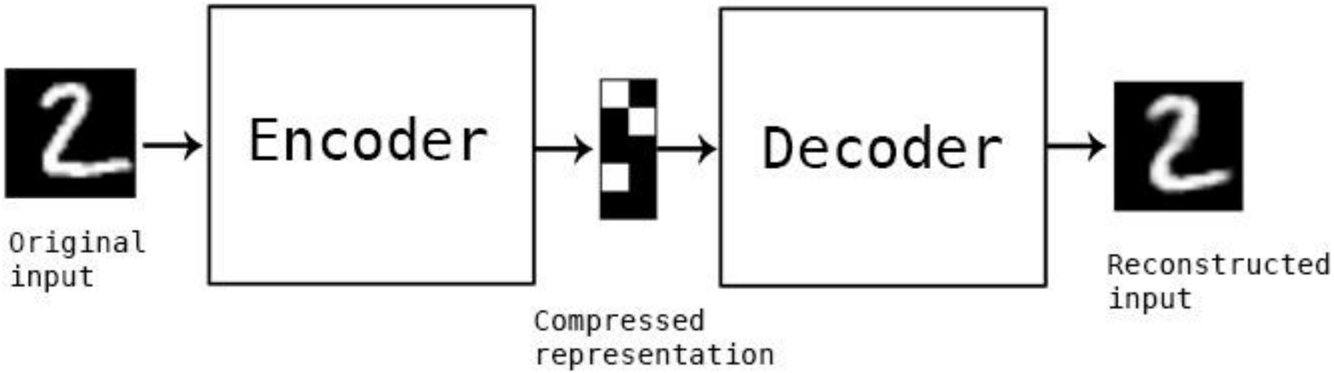
Machine Analysis: Auto-Encoders

- Auto-encoders

Human-aided document analysis

Machine Analysis: Auto-Encoders

- Auto-encoders



Human-aided document analysis

Machine Analysis: Auto-Encoders

- Denoising auto-encoders

Human-aided document analysis

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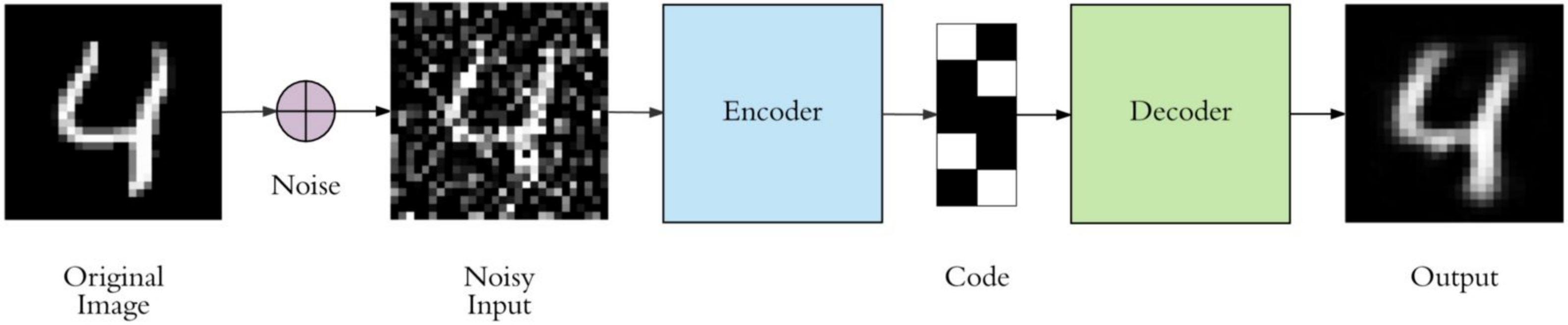

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Machine Analysis: Auto-Encoders

- Selectional auto-encoders

Human-aided document analysis

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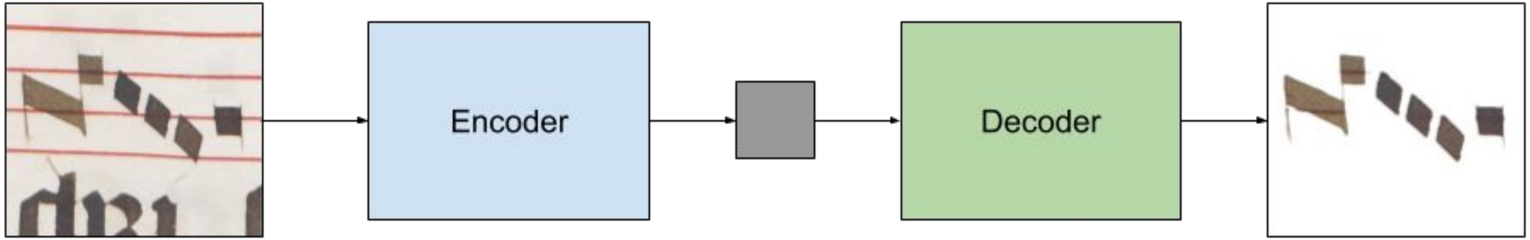

Human-aided document analysis

Machine Analysis: Auto-Encoders

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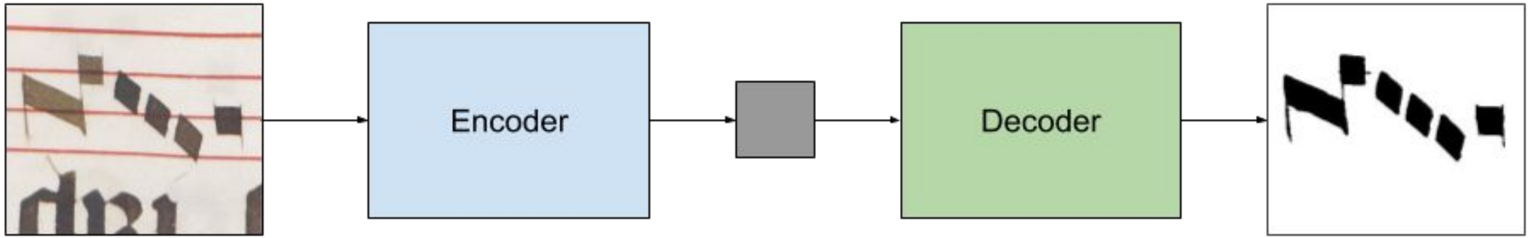

Human-aided document analysis

Machine Analysis: Auto-Encoders

- Class-wise selectional auto-encoders for document processing

Human-aided document analysis

Machine Analysis: Auto-Encoders

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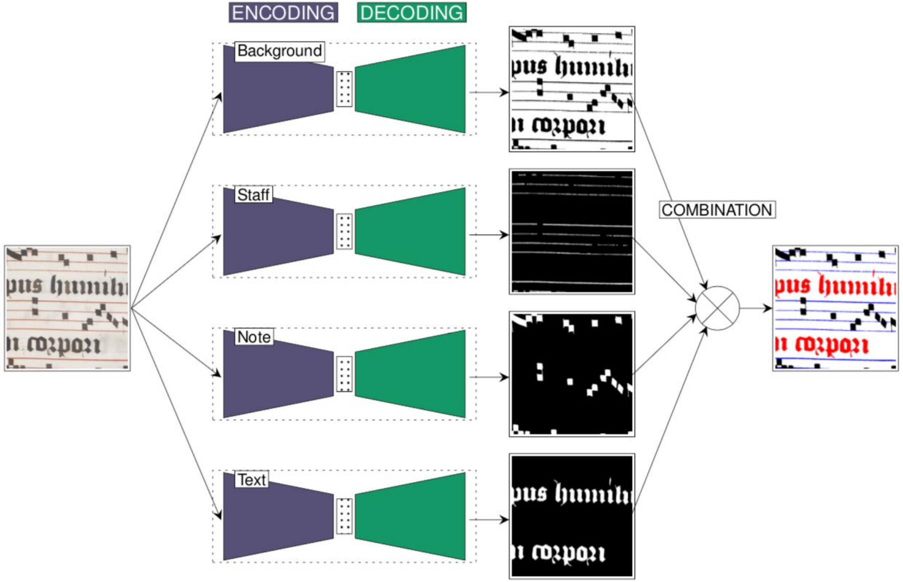

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Machine Analysis: Auto-Encoders

- Patchwise CM
  - Advantages
    - Fast document processing
    - Class-wise independent detection
  - Disadvantages
    - Demanding ground-truth data

Human-aided document analysis

Machine Analysis

	Accuracy	Time per page
Pixelwise CM	~ 90 %	~ 6 hours
Patchwise CM	~ 92 %	~ 1 minute

Human-aided document analysis

Human Teaching

- User is in charge of teaching what needs to be done
- In practice: manual separation of document layers to create ground-truth data

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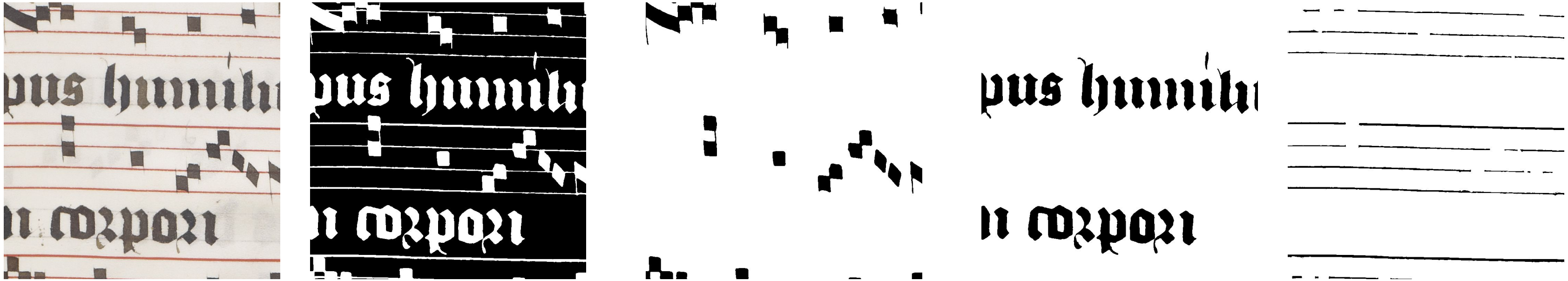


Human-aided document analysis

Human Teaching

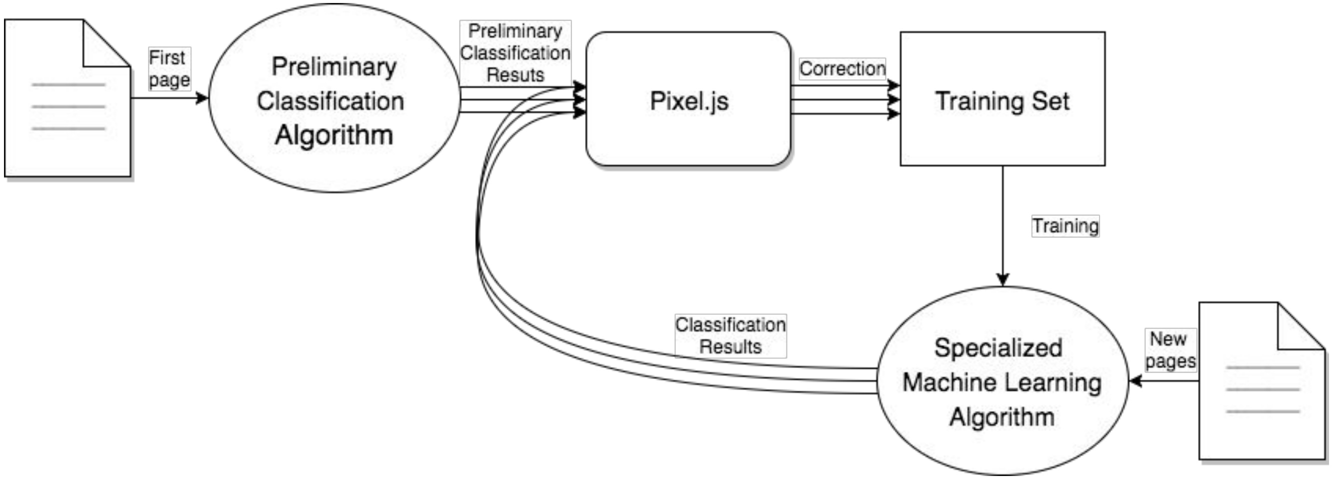
- Models need manuscript-specific training
  - Some cross-manuscript adaptation is possible but not reliable
- It is necessary to integrate the annotation tool into the workflow
- Development of Pixel.js

Human-aided music document analysis

Overview

Human-aided music document analysis

Overview



Human-aided music document analysis

Specialization

- Model re-training is costly
  - Training neural networks requires time
  - Other (adaptive) models are less accurate and slower in classification
  - Trade-off among adaptiveness, efficiency, and accuracy
  - Experiments are to be carried out
- Straightforward solution: assume asynchronization
  - User may do other duties while the machine is learning

Conclusions

Summary

- Universal OMR is not feasible in the short term
- Generic workflow can be assumed
- Human-aided OMR is appealing
- Users provide guidance to the system wherever necessary
    - Correct remaining errors
    - Continuous teaching to improve future performance

Conclusions

Summary

- The document analysis stage is the first task to address in the OMR workflow
- New issues to take into account
  - Learning-driven models
  - Annotations tools
  - Processing time

Conclusions

Discussion

- Towards general and adaptive OMR workflow
- Users do not need technical knowledge to provide guidance
- Lower performance bound than manuscript-specific OMR systems

Conclusions

Discussion

- Environment for Machine Pedagogy: learning how to teach the computer
- Relevance of the user
    - Initial model selection
    - Identification of promising ground-truth data

Conclusions

Future work

- Primary goal: to reduce human effort
  - Domain adaptation techniques
  - Improving accuracy of the models
  - Make the workflow be as friendly as possible

Thank you!

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