Pixelwise classification for music document analysis

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Introduction

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- Music archives and libraries preserve music over the centuries
- Computational tools for music analysis are of great interest

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- Manual transcription from source implies a high cost

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- Computational tools for music analysis are of great interest
- Large amounts of content in symbolic format are required
- Manual transcription from source implies a high cost
- Automatic transcription systems become valuable tools

Introduction

Optical Music Recognition (OMR)

- From score image to symbolic encoding

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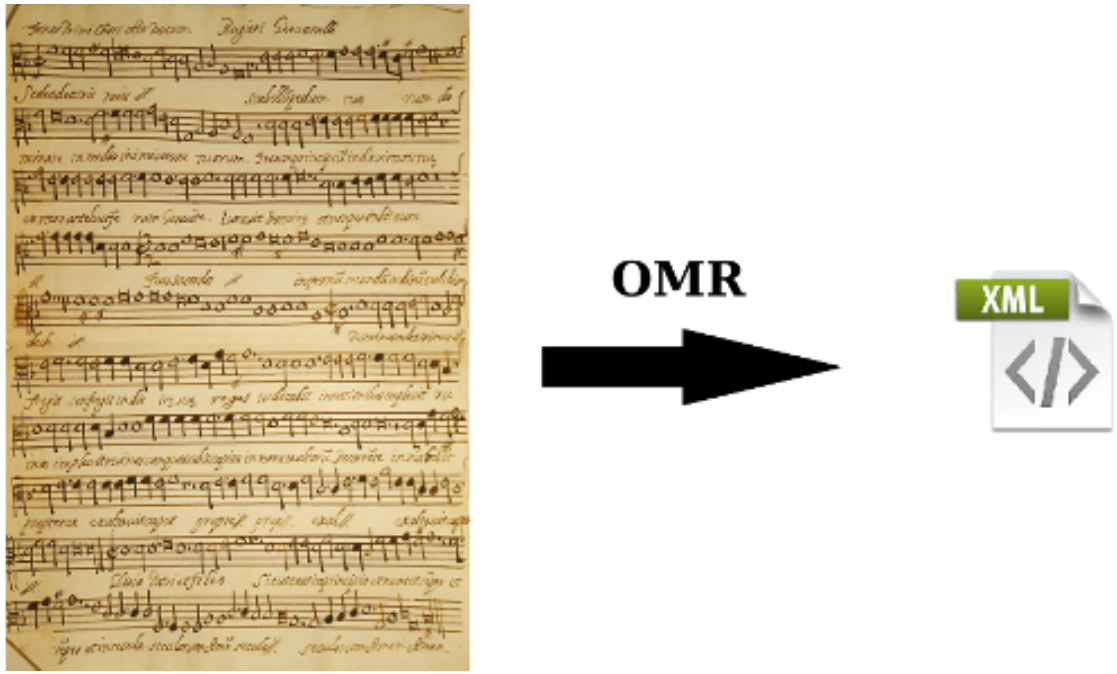
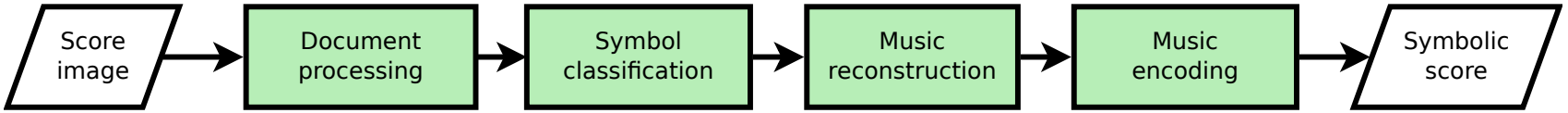


Introduction

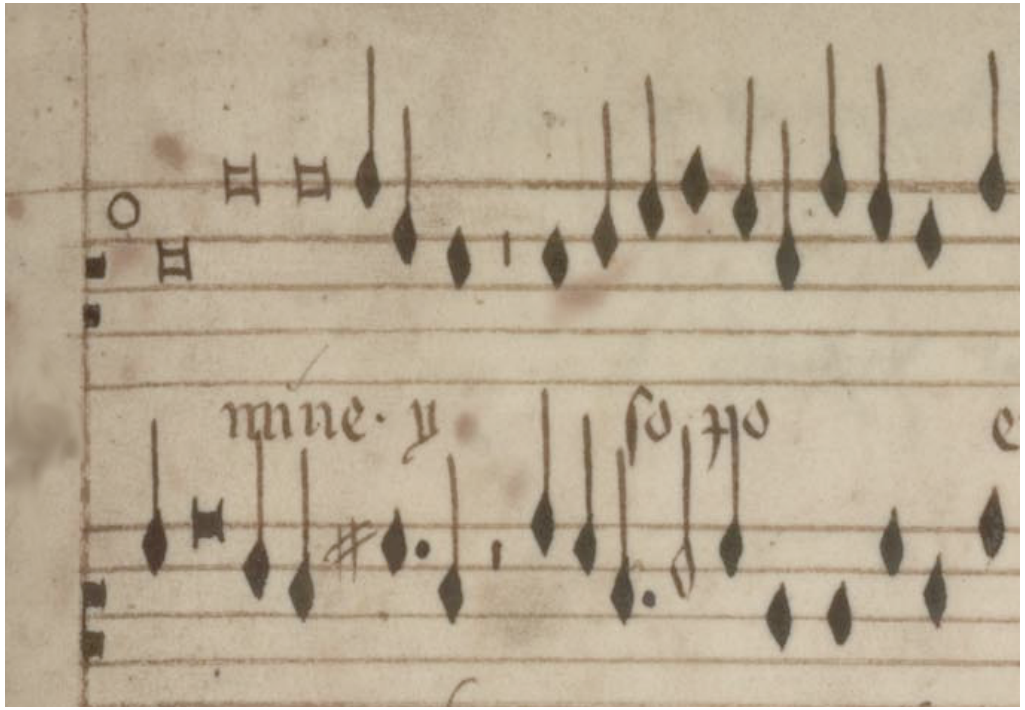
Optical Music Recognition (OMR)

- Several interdisciplinary steps



Introduction

- Most document-processing stages focus on *content separation*:



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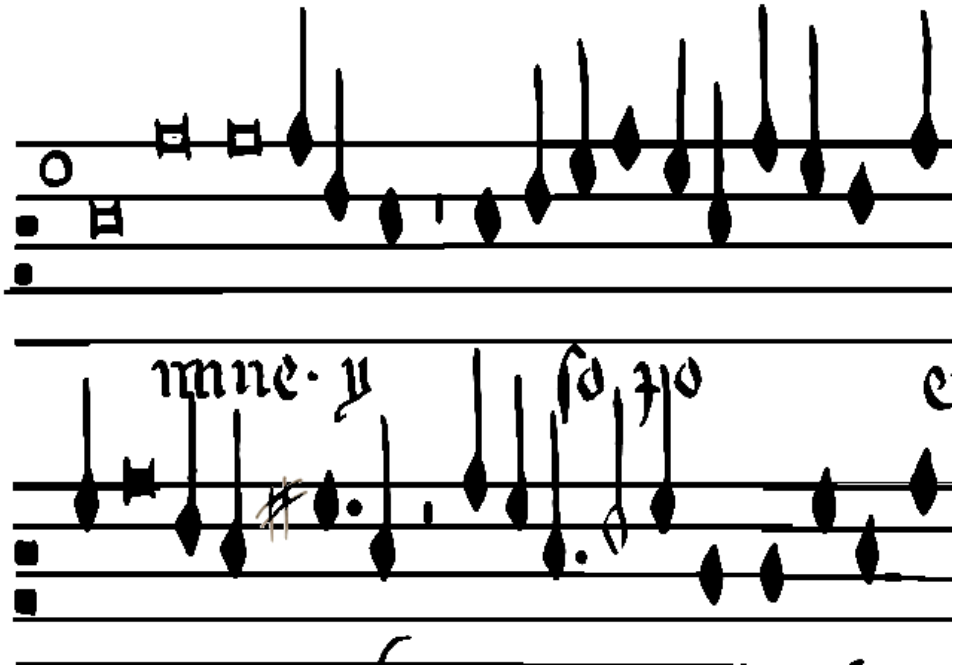

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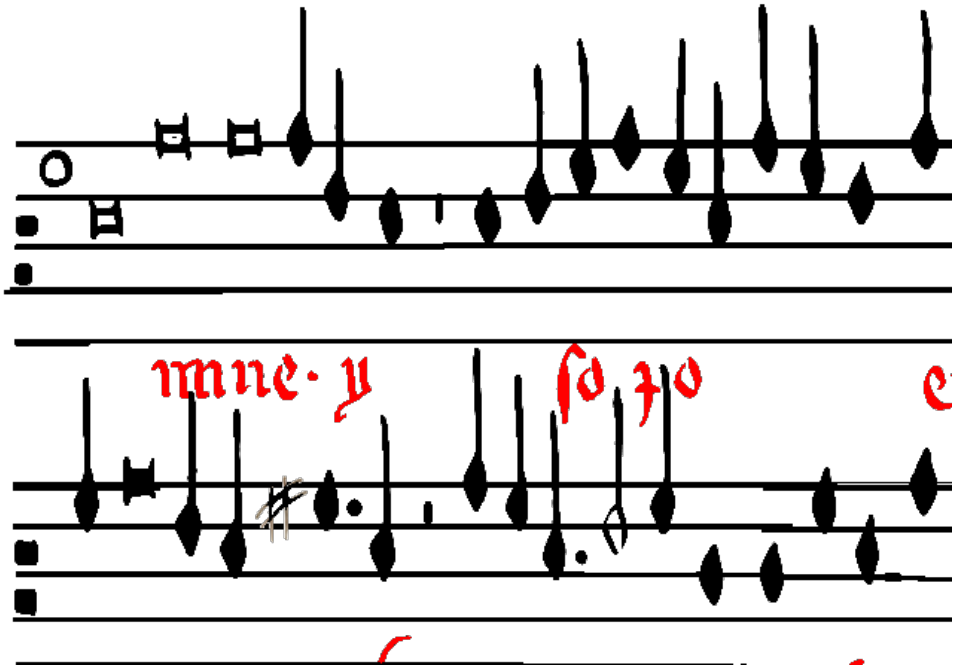

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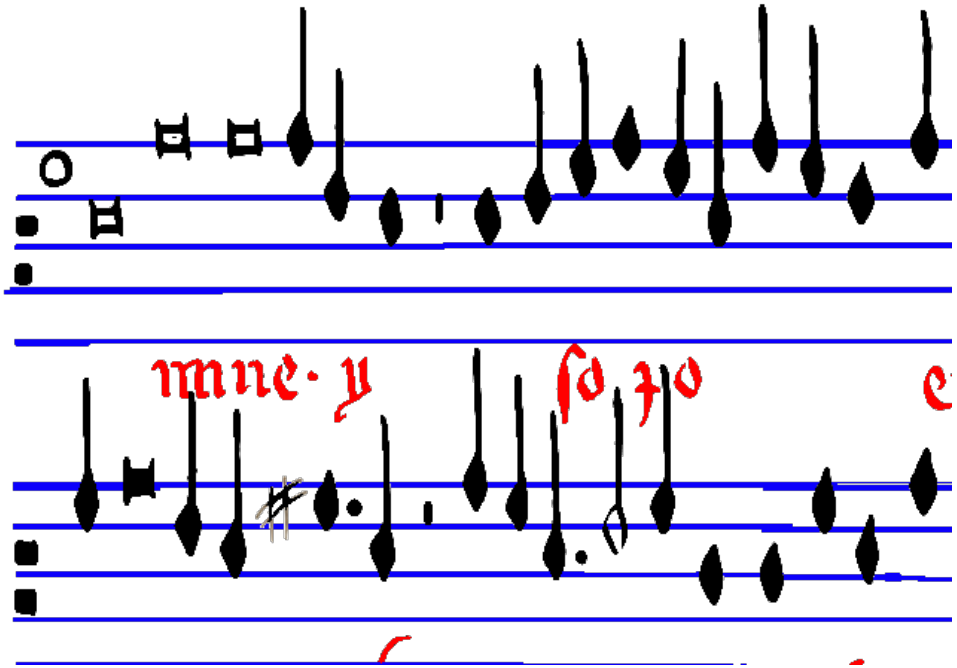
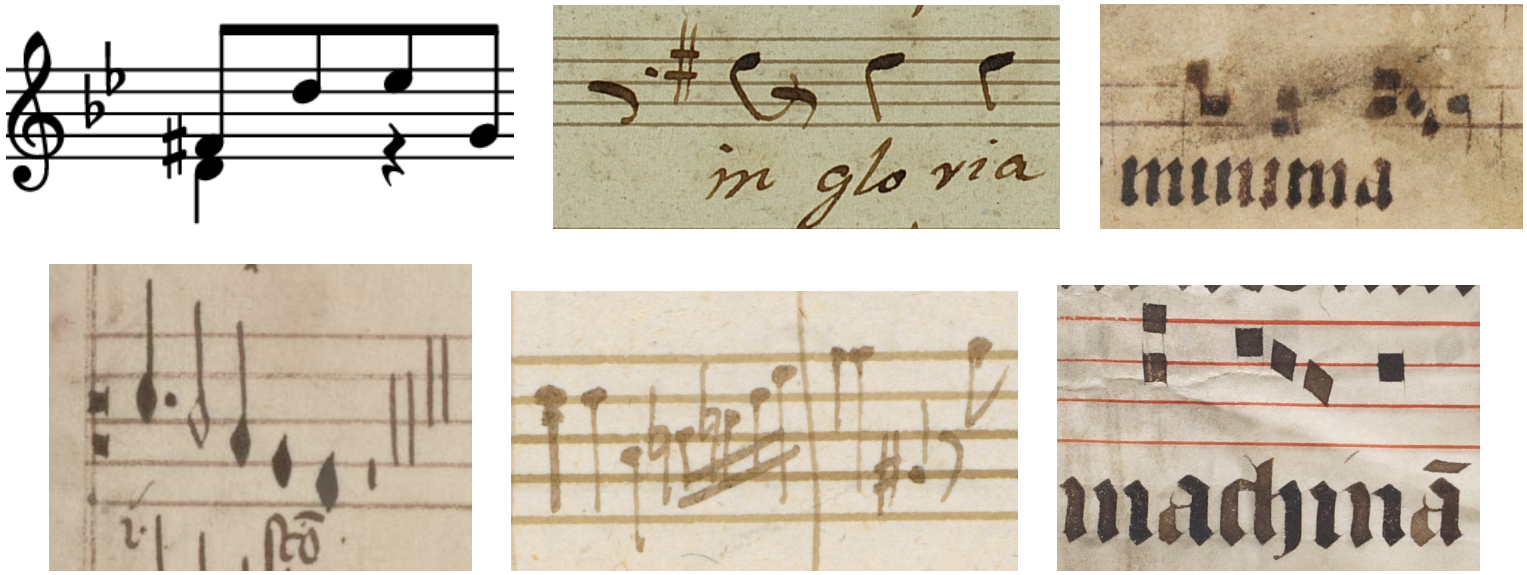


Introduction

- Poor generalization of the existing strategies
- Music documents have a high level of heterogeneity



Introduction

Framework

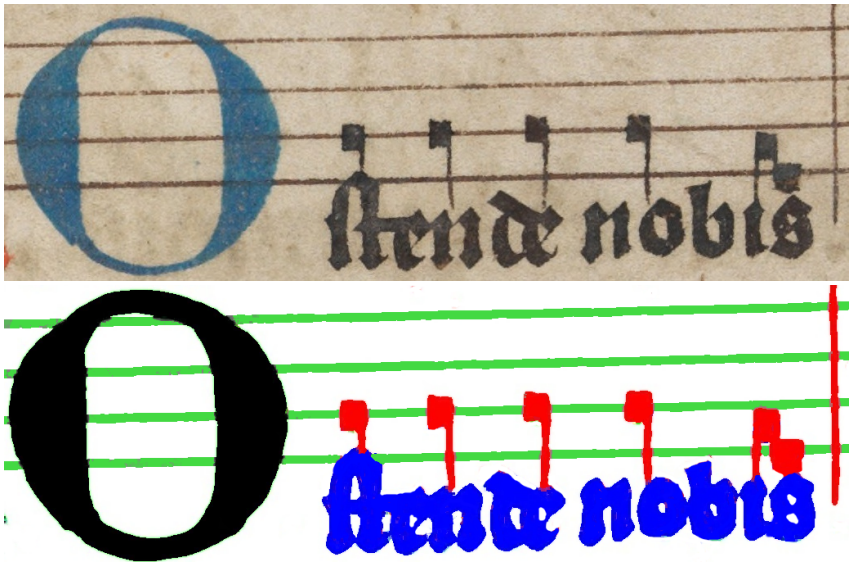
- Machine learning framework for music document processing
- Regardless of the specific characteristics of the source
- Detection of the different layers at the same time

Framework

Framework

Pixelwise classification approach

- Categorization of each pixel within the input image



- Allows detecting small and thin elements present in music notation

Framework

- Machine learning for avoiding hand-crafted procedures

Framework

- Machine learning for avoiding hand-crafted procedures
- We make use of Convolutional Neural Networks (CNN)
  - Great performance in image-related tasks
  - Good generalization

Framework

Convolutional Neural Networks

- Series of hierarchical transformations (convolutions)
- Transformations not fixed but learned through training
- Less dependent on human intervention

Framework

Pixelwise classification

- Straightforward approach: classify every single pixel of the input image

$$I(x, y) \rightarrow \{\text{background}, \text{staff line}, \text{symbol}, \text{text}, ...\}$$

Framework

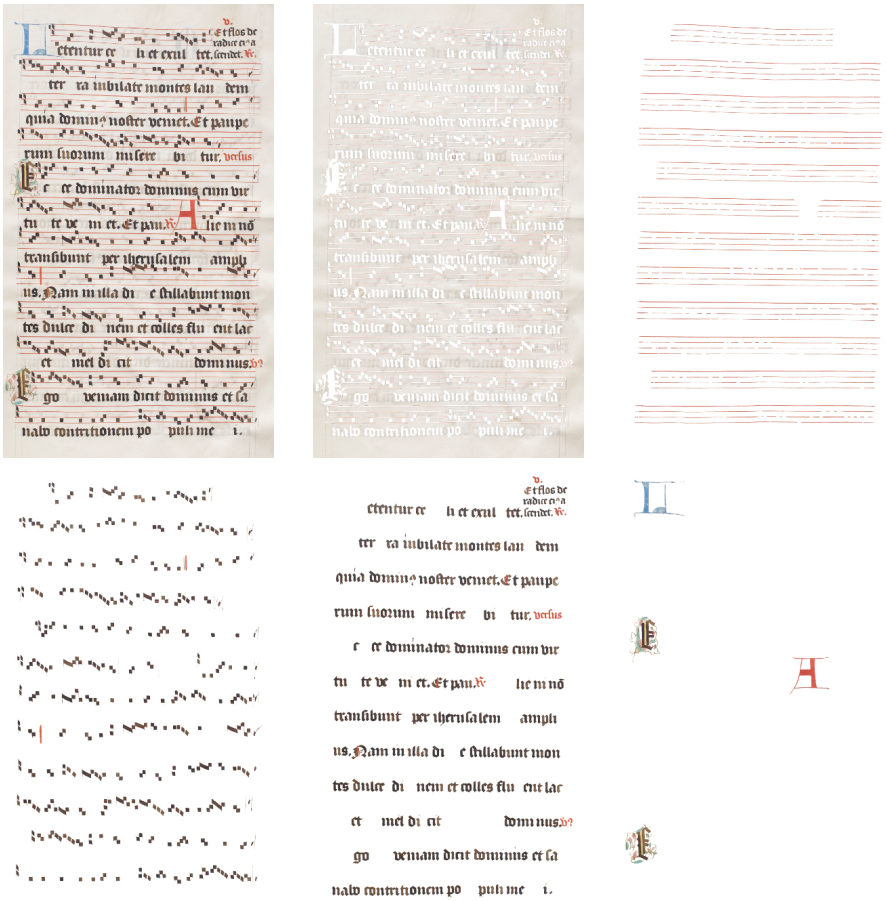
Pixelwise classification

- To train the CNN we need ground truth
  - Documents whose categories have been correctly separated

Framework

Pixelwise classification

- Ground-truth example[1]
  - One page ∼ 30 million pixels

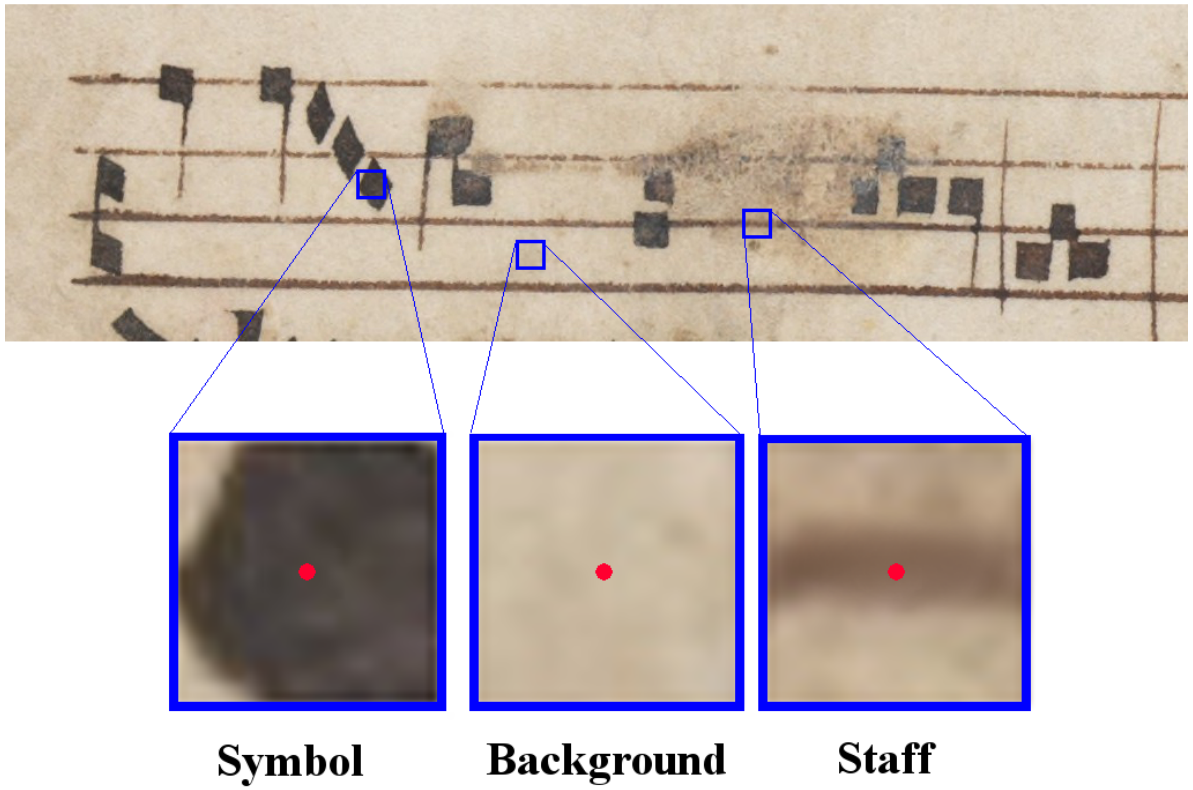


[1] Salzinnes Antiphonal manuscript (CDM-Hsmu M2149.14)

Framework

Pixelwise classification

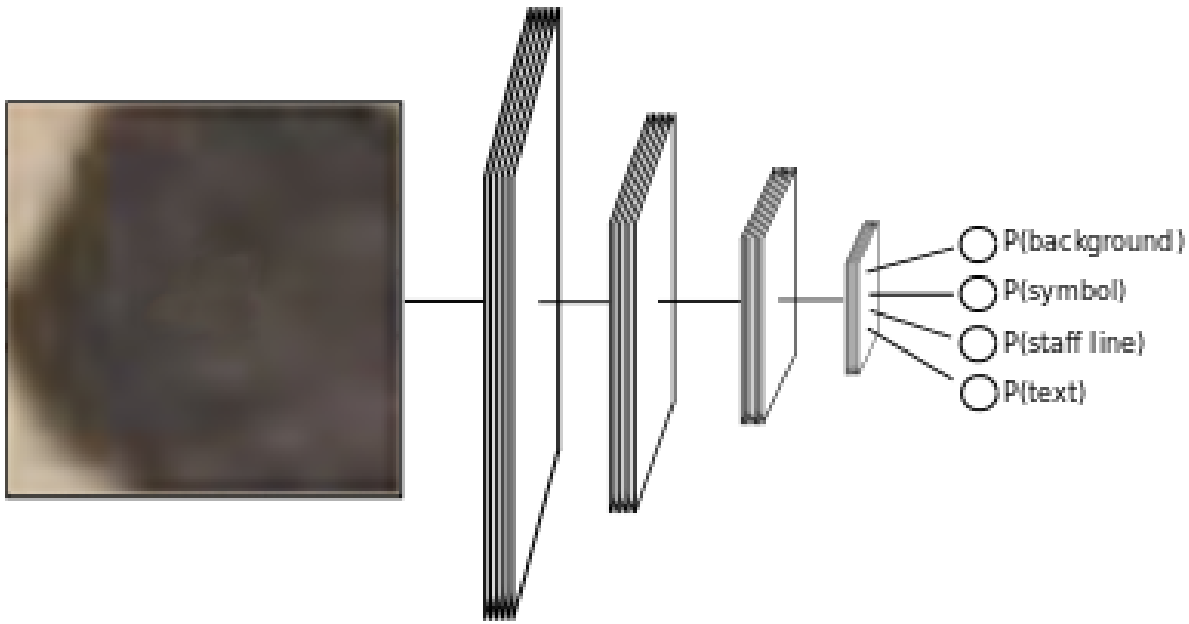
- CNN is provided with the surrounding region of the pixel to be classified



Framework

Pixelwise classification

- Estimation of a probability for each possible category



Framework

Pixelwise classification

- Relevant issues

Framework

Pixelwise classification

- Relevant issues
  - Ground truth creation

Framework

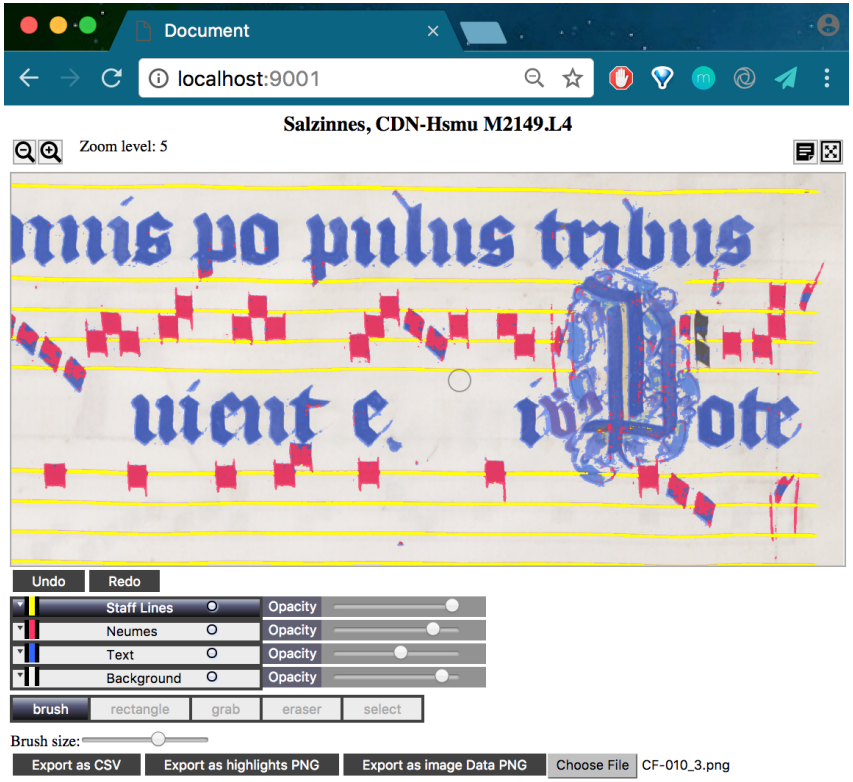
Pixelwise classification

- Relevant issues
  - Ground truth creation
    - Pixel.js

Framework

Pixel.js

- Web-based tool for ground truth creation



Framework

Pixelwise classification

- Relevant issues
  - Ground truth creation
    - Pixel.js

Framework

Pixelwise classification

- Relevant issues
  - Ground truth creation
    - Pixel.js
  - Computational cost

Framework

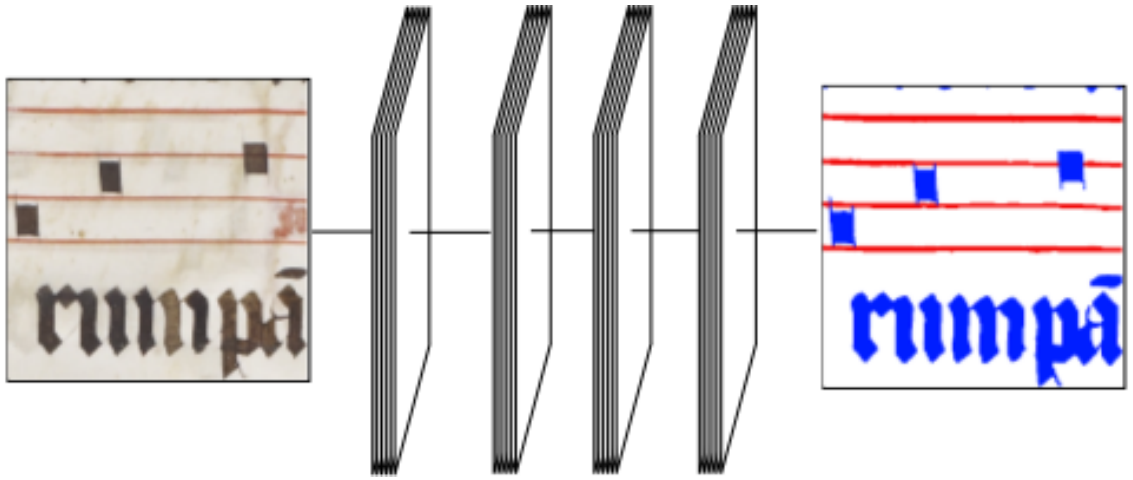
Pixelwise classification

- Relevant issues
  - Ground truth creation
    - Pixel.js
  - Computational cost
    - Image-to-image approach

Framework

Image-to-image classification

- Image-to-image pixelwise classification
  - Classify a whole region at the same time



  - We need to split the document into patches of equal size

Framework

Image-to-image classification

- Similar accuracy
- Much more efficient (from several hours to few minutes)
- Usually needs a bigger training set

Deployment

Deployment

General use

- Full workflow for a new type of document
  - Ground-truth creation with Pixel.js
  - Model training and document processing as Rodan jobs

Deployment

Resources

- Training models: very slow, need of high-performance computing
- Classification: fast with the image-to-image approach

Deployment

DEMO

Conclusions

Conclusions

Summary

- Generalizable music document analysis with machine learning
- Research on effective and efficient strategies
- Usability through Rodan framework

Conclusions

Future work

- Integrate with the rest of the OMR workflow
- Make efforts towards faster adaptation to new document types
  - Efficient ground truth creation with Pixel.js
  - Study of model adaptation techniques

Thank you!

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WESTGRID

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