Seeing History

The Visual Side of the Digital Turn

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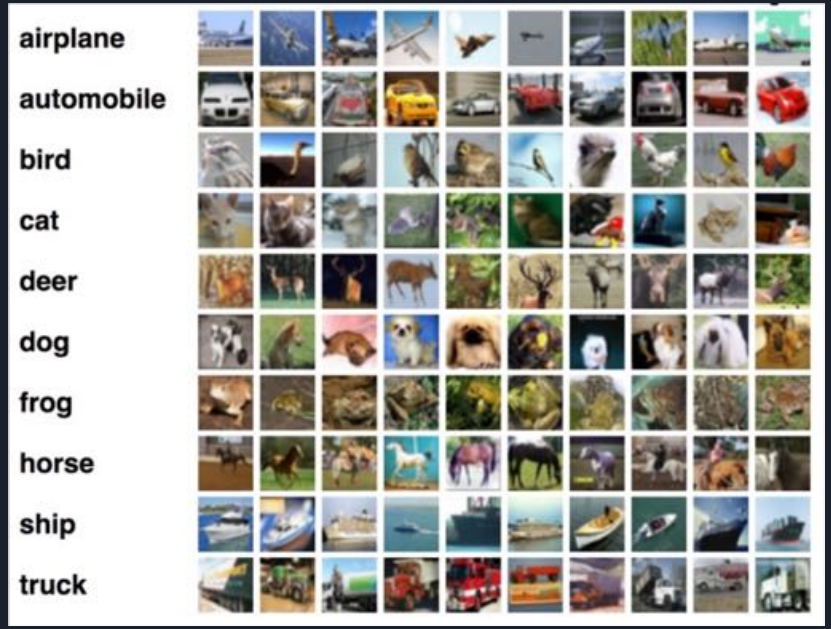
Introduction

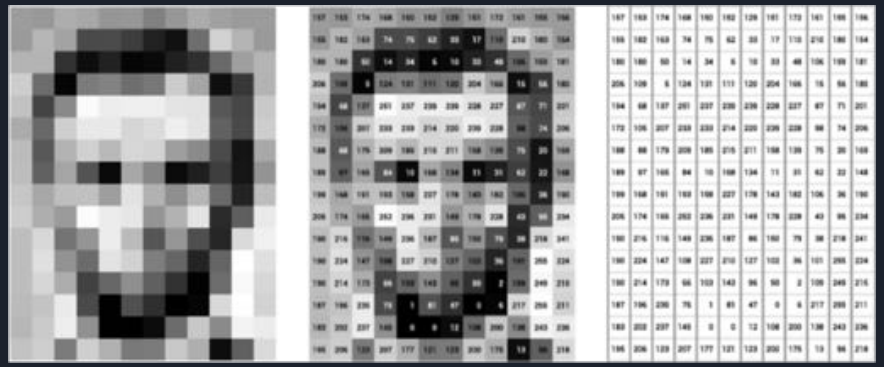
- The Digital Humanities are too text-heavy
- Large collections of visual material, limitations of searching with OCR
- Researcher-in-Residence at National Library of the Netherlands
- How can computers help us to explore and analyze large collection of historical visual material?

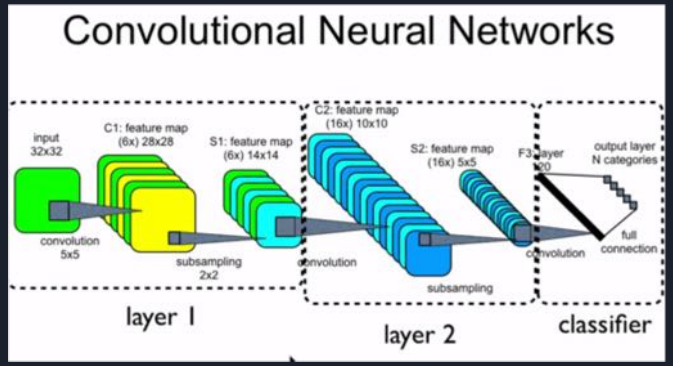
Computer Vision

- Computer Vision - gain high-level understanding of images
- Object detection
- Convolutional neural networks



From an image to a neural network





Convolutional neural networks on historical visual material

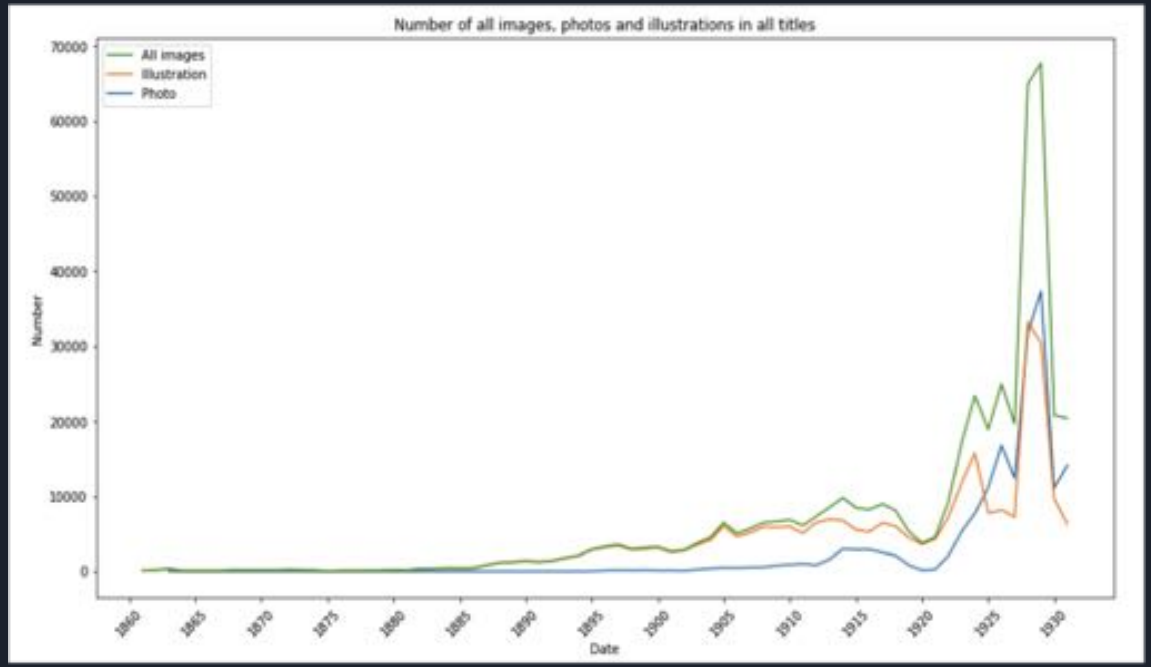
- Two datasets extracted from Delpher
  - CHRONIC (452,543 images of the news 1860-1930)
  - SIAMESET (426,000 historical advertisements 1945-1995)

- Three approaches
  - Detecting medium-specific features (separating photographs from illustrations)
  - querying images based on abstract visual aspects (clustering visually similar advertisements)
  - Training a neural network based on visual categories developed by domain experts

Approach I: Medium-specific characteristics

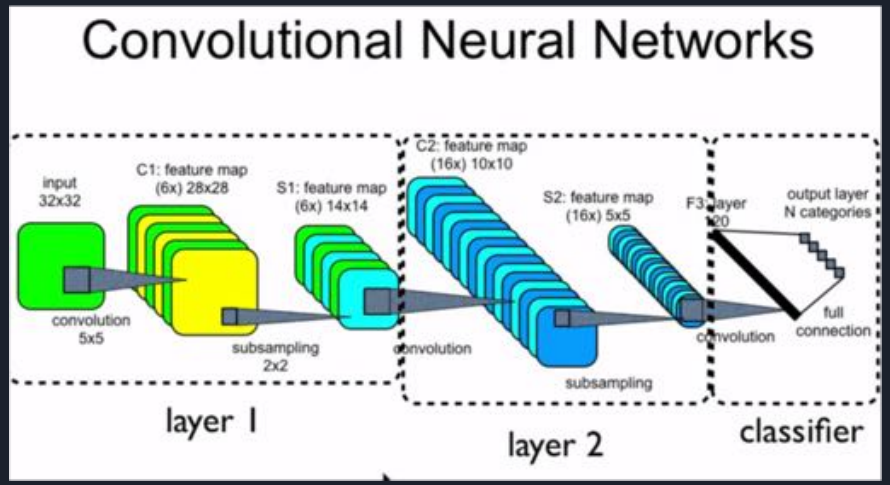
- Research the transition between the use of illustrations and photographs by newspapers to visualize the news
- Classify images of CHRONIC as either illustration or photograph (F1-score: 0.9)

Approach I: Medium-specific characteristics



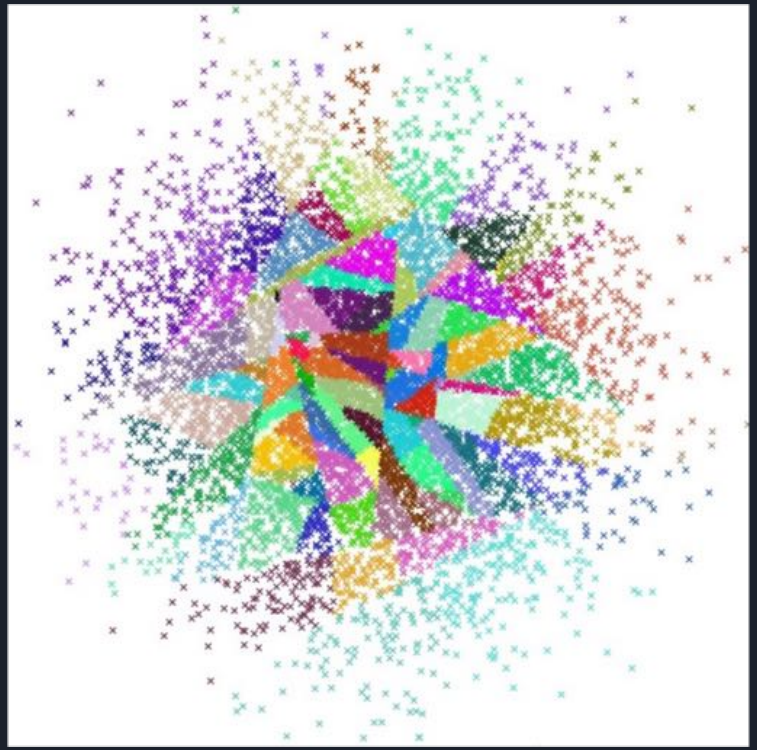
Approach II: SIAMESE

- Can we use convolutional neural networks to trace visual change in historical advertisements?
- Object detection for historical images is sub-optimal



Approach II: Cluster on visual similarity

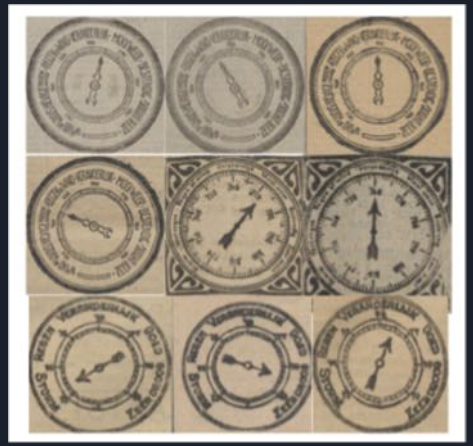
- Select image in penultimate layer
- Cluster in multidimensional space based on 2,048 visual aspects
- Find nearest neighbors in clustered space

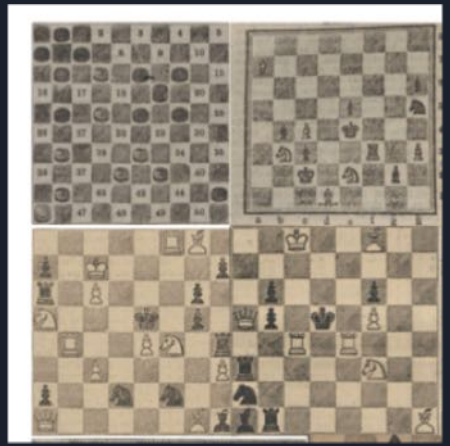


Approach II: Style of advertising

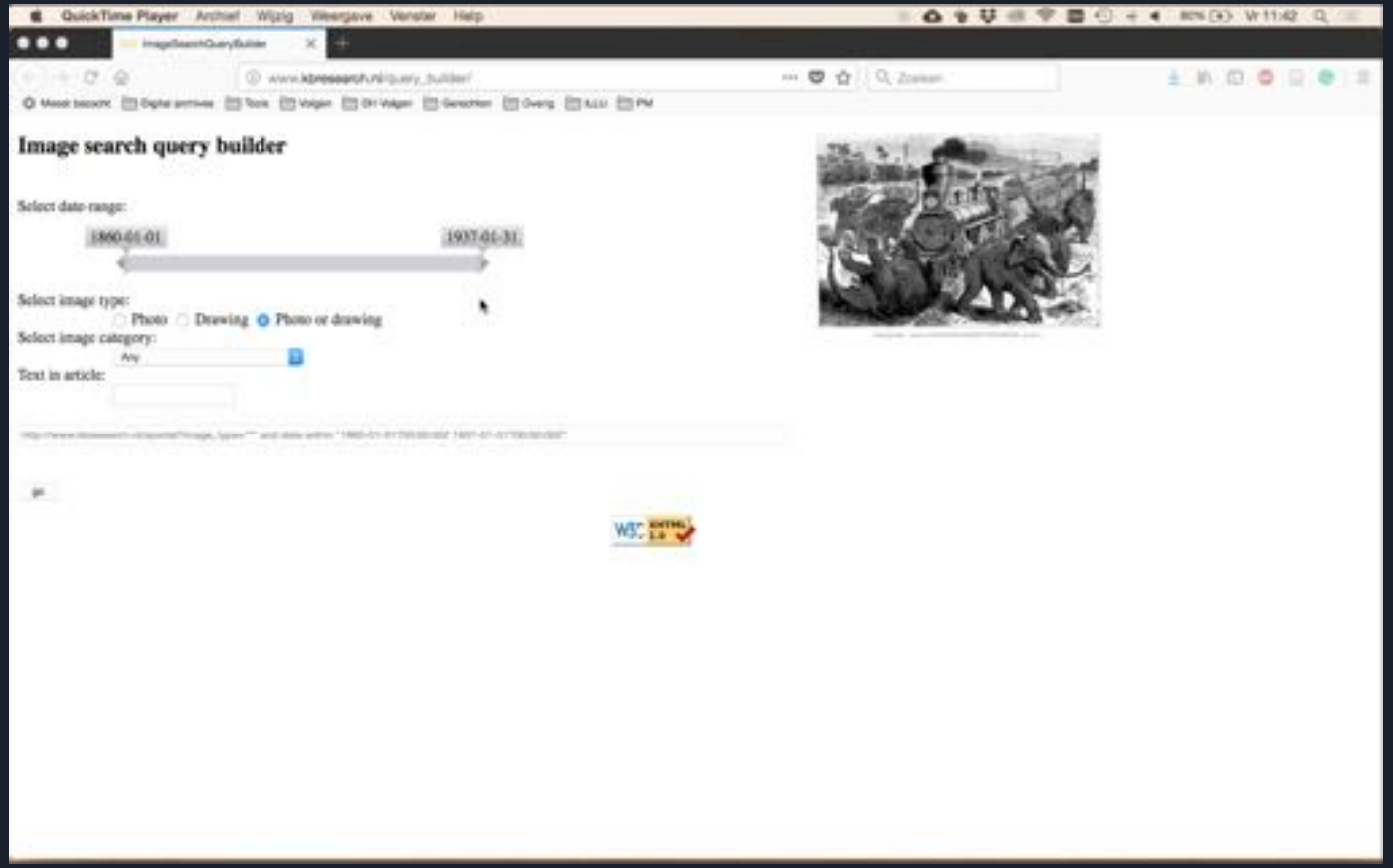
Approach III: Building your own classifiers

- Recognize nine relevant categories: buildings, cartoons, chess, crowds, logos, maps, schematics, sheet music, and weather reports
- Similar to OCR → provides direct access to visual content
- Visual similarity ≠ stylistic similarity ≠ conceptual similarity





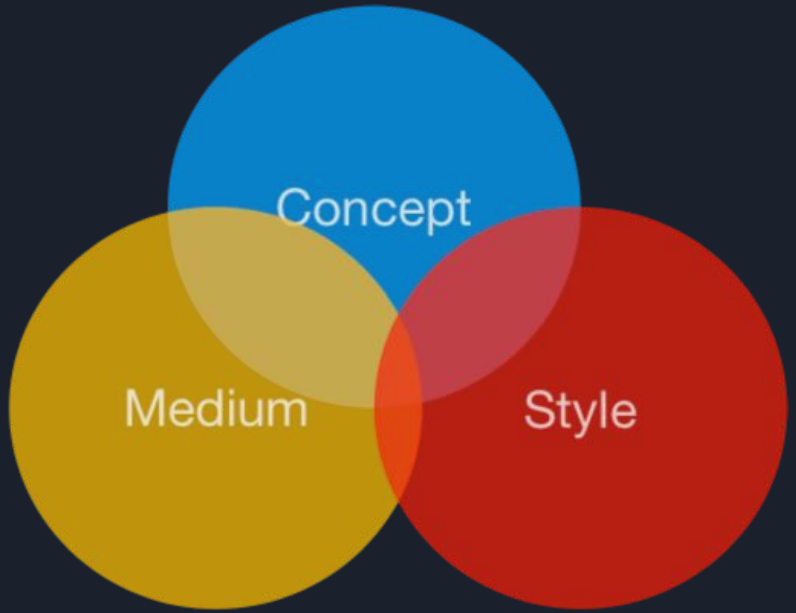
Approach III: Building your own classifiers



Conclusion: Opportunies

- CNNs offer opportunities for:
  - collection specialists
  - (digital) humanities researchers
- Explore and analyze large collections of visual sources

Conclusion: 1) Structures of Visual Similarity



Conclusion: 2) Historicity of images

Conclusion: Studying Images and Text in Conjunction

ImageTexts

Studying Images and Texts in Conjunction

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Research Question

The recent upsurge of large-scale analysis of visual material (Computer Vision) shifts the focus in Digital Humanities research away from texts. However, this has also led researchers to approach text and images as disjointed entities. **We analyze similarity and change in both textual and visual elements of car advertisements extracted from digitized newspapers.** By juxtaposing change over time in text and visual material, we aspire to show that the meaning of imagetexts can be studied by looking at the relation between the two forms of representation.

Dataset

Our dataset consists of 9,863 the advertisements for cars extracted from the Dutch newspaper *De Volkskrant* between 1945 and 1995. These advertisements have a visual and a textual component (see Fig. 1).

Fig. 1: Automobile advertisements from Volkskrant

Results: texts

Burstiness in ads increased and ten change points could be identified (see fig. 2). Periods of burstiness correspond to particular themes, such as fuel efficiency, environment, safety, and gadgets (see fig. 3)

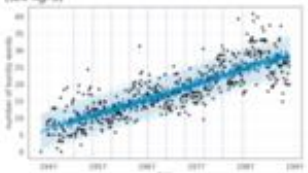

Fig. 2: Average Monthly Burstiness and change points in burstiness

50s-60s	70s	80s	90s
[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]

Fig. 3: Selection of Bursty words in the five decades of the dataset

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