Seeing History

The Visual Side of the Digital Turn

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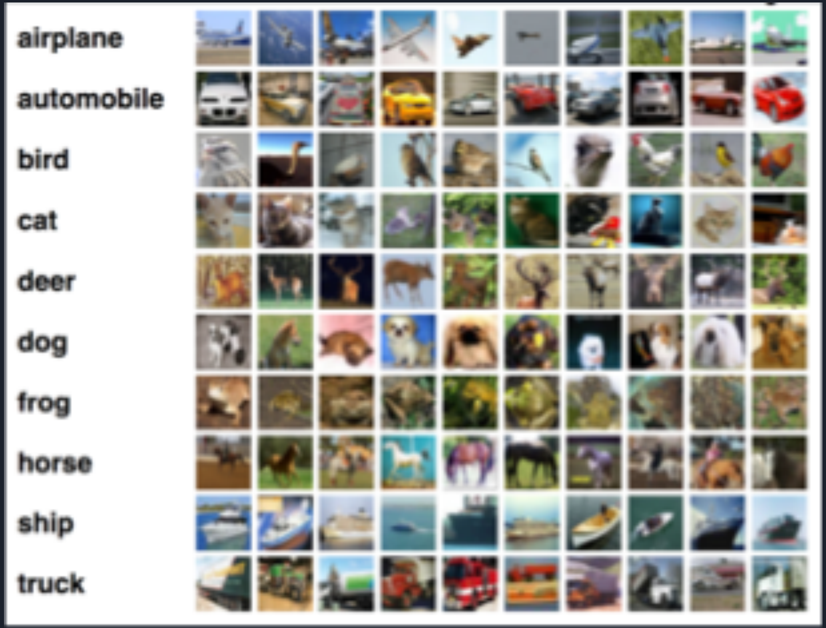
Introduction

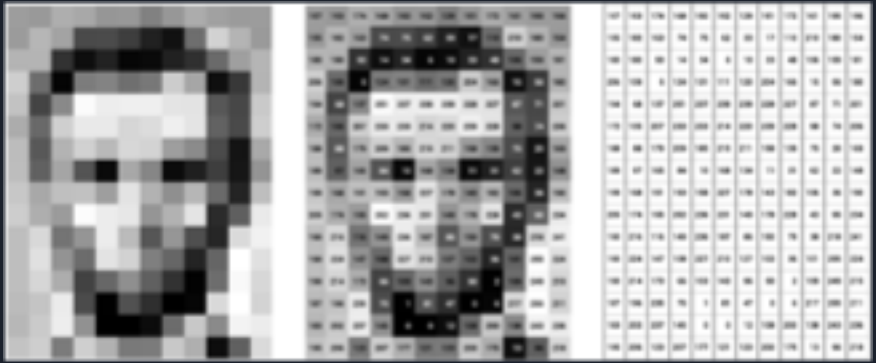
- The Digital Humanities are too text-heavy
- Large collections of visual material, limitations of searching with OCR
- Researcher-in-Residence at National Library of the Netherlands
- How can computers help us to explore and analyze large collection of historical visual material?

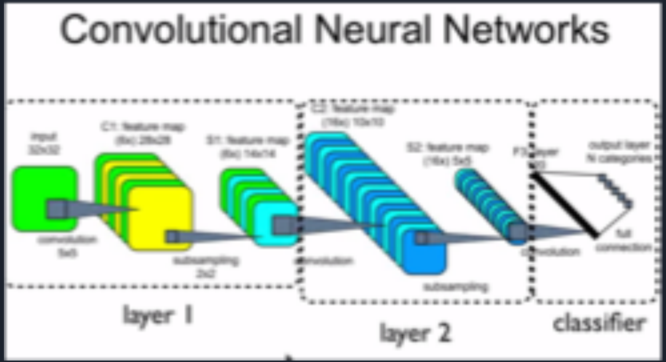
Computer Vision

- Computer Vision - gain high-level understanding of images
- Object detection (ImageNET)
- Convolutional neural networks
- Availability increased with open-source frameworks Tensorflow (Inception-V3 model) and Keras



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)

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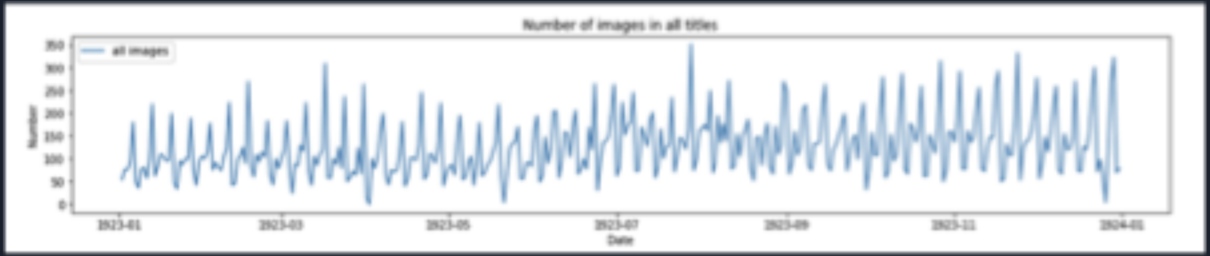
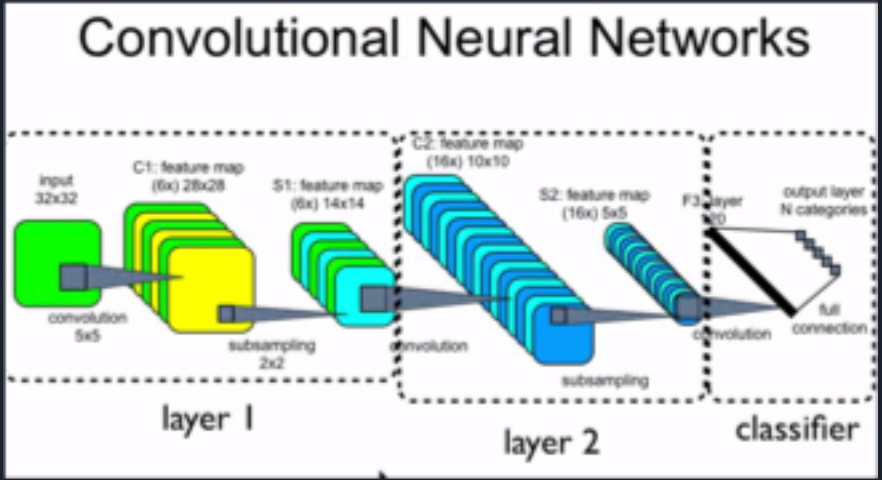


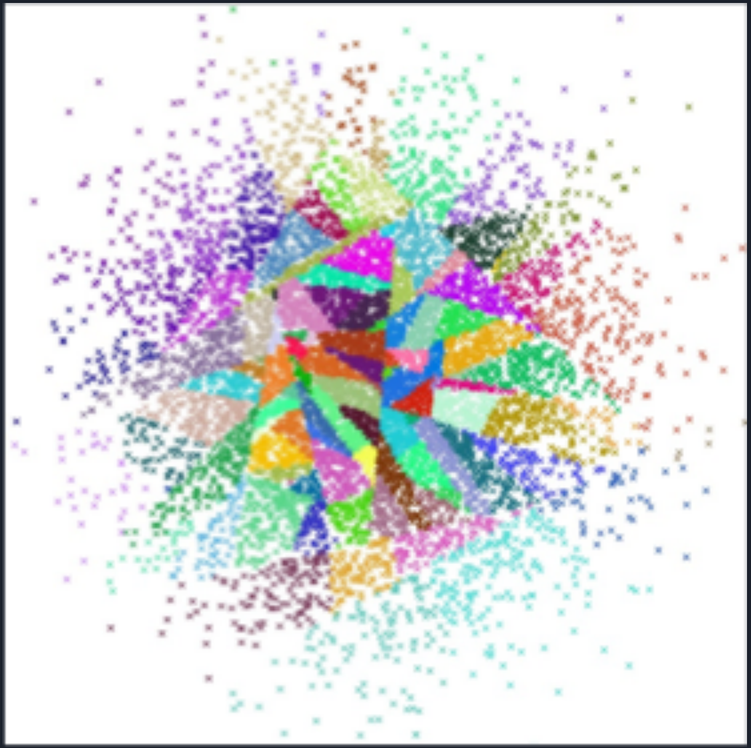
Approach II: SIAMESE

- 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
- Timeline with with most similar images per year



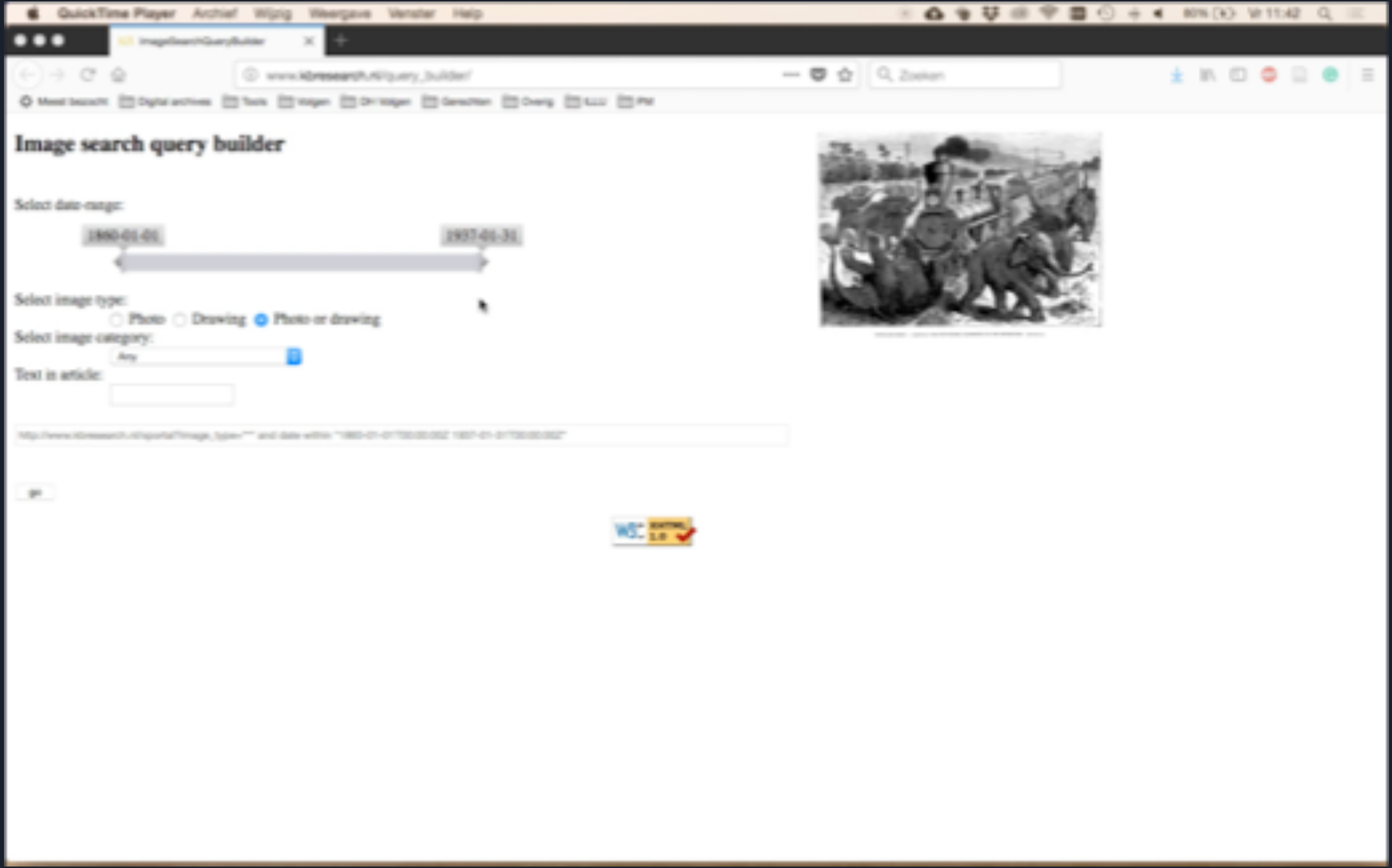
Approach II: Changing representation of cars

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

- CNNs offer opportunities for:
    - collection specialists
    - (digital) humanities researchers
- Explore and analyze large collections of visual sources/
- How can the humanities help computer scientists?
    - What do we talk about when we talk about visual similarity?
- Major challenge
    - Separation text and images

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