

OBJECT RECOGNITION IN ART DRAWINGS

TRANSFER OF A NEURAL NETWORK

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ICASSP 2016, 23 March, Shanghai



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UNIVERSITY OF CALIFORNIA



Ingrid Daubechies



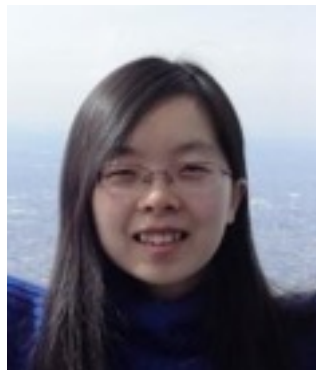
Mauro Maggioni



Elizabeth
Honig



Eric Monson



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Jan Brueghel Complete Catalog

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"Brueghel Family: Jan Brueghel the Elder." The Brueghel Family Database. University of California, Berkeley. <http://janbrueghel.net/> (accessed January 24, 2016).

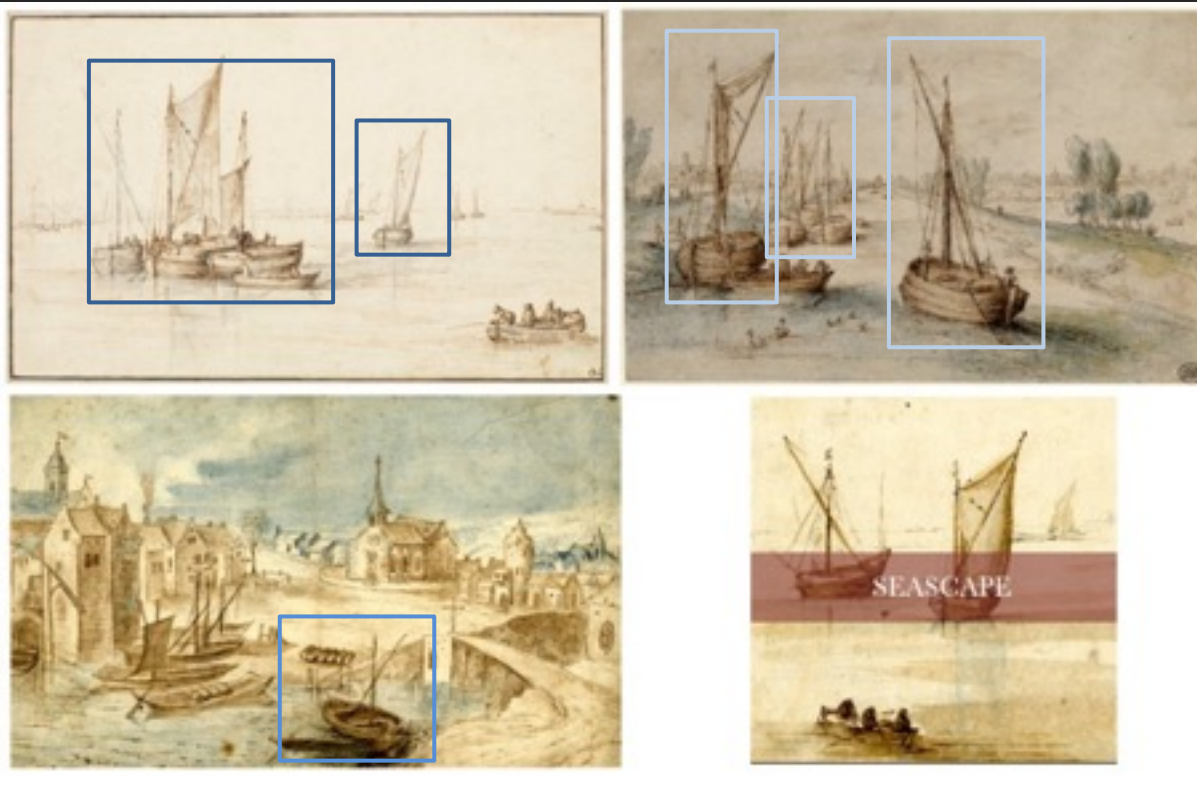


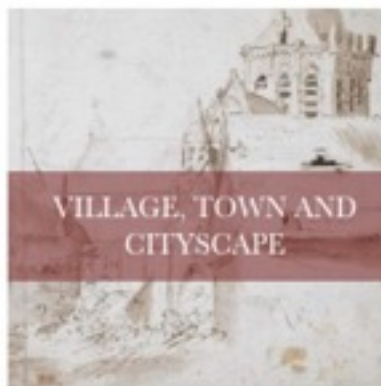
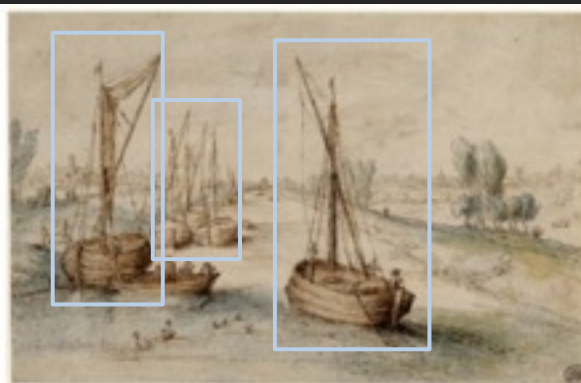
ABOUT JAN BRUEGHEL

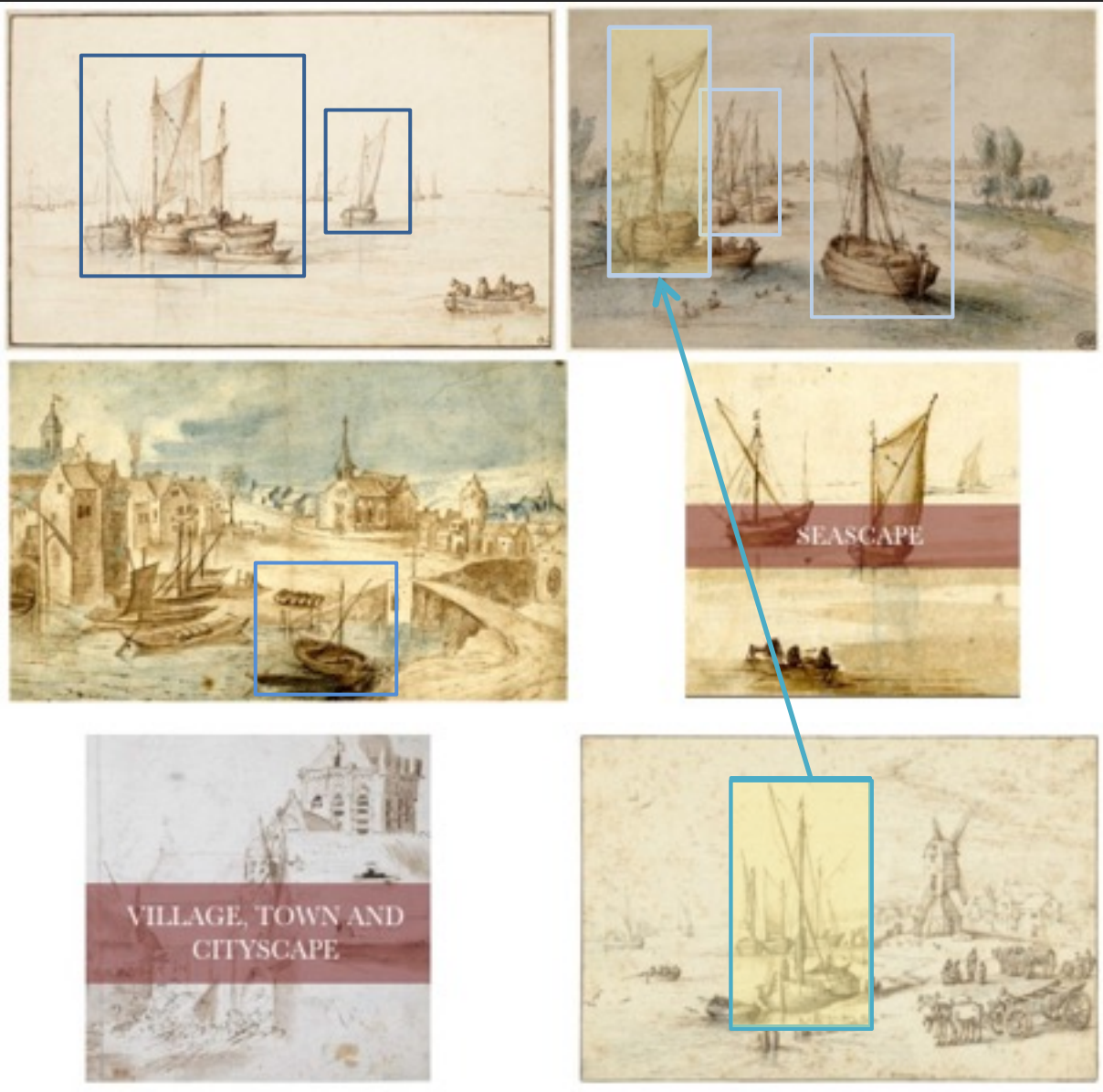
Jan Brueghel (1568/9-1625) was a painter of immense diversity. His work includes biblical, mythological, and classical histories, battle scenes, hellscapes, seascapes, floral garlands and still lifes, portraits and genre scenes, as well as many sorts of landscape: woodland hunts, mountain prospects, country roads and rivers, and villages. While his surviving oeuvre consists of about 350-400 autograph paintings (including collaborative works), hundreds more are, to varying degrees, associated with his hand or his conception. Early in his career Jan worked mostly at a small scale and on a copper support; gradually the size of his pictures increased and he worked more often on panel or even on canvas. Brueghel often collaborated with other master painters, including Peter Paul Rubens, Hans Rottenhammer, Hendrick van Balen, Sebastiaen Vrancx, and Joos de Momper. He only had two known pupils, Daniel Seghers and his own son Jan the Younger, but an efficient studio staffed by paid professionals permitted copious production.

[Read more](#)









SEE ALL
PAINTINGS

SEE ALL OIL
SKETCHES

SEE ALL
DRAWINGS

SEE ALL
PRINTS



compute SIFT



match feature with bounded spatial
distortion*

*Y. Lipman et al, 2014

where SIFT falls

compute SIFT



match feature with bounded spatial distortion*

*Y. Lipman et al, 2014



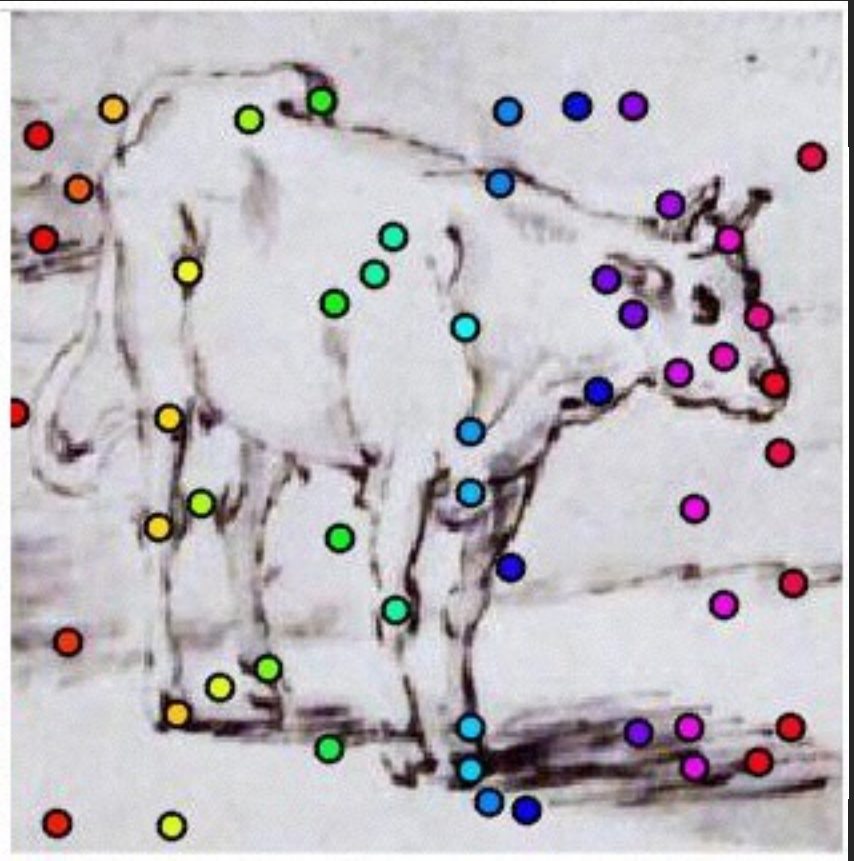
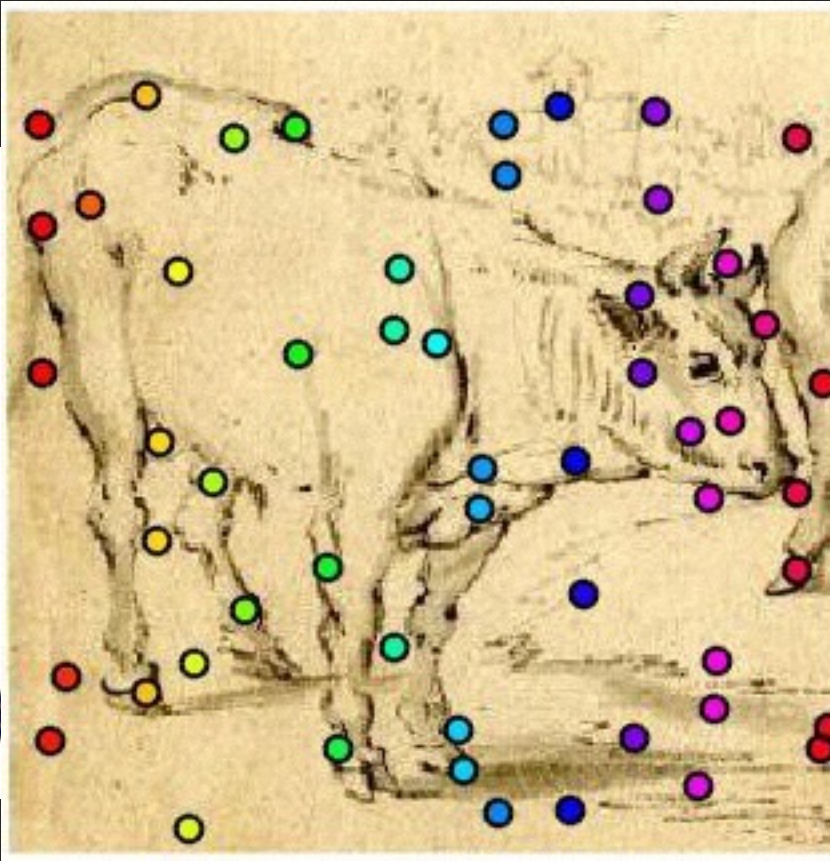
where SIFT fails

compute SIFT



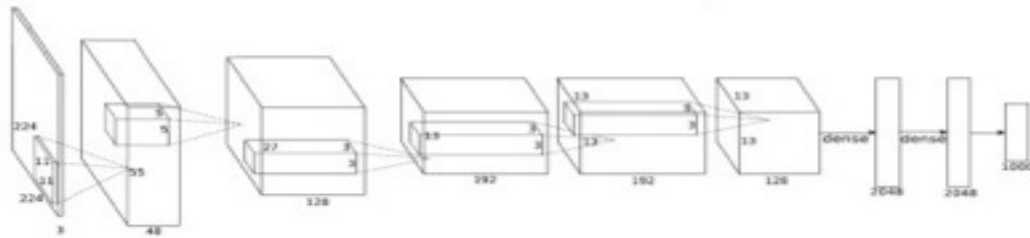
match feature with bounded spatial distortion*

*Y. Lipman et al, 2014



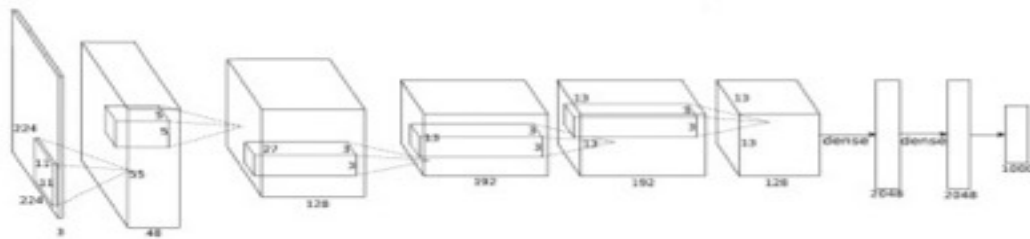
where SIFT falls

- flexibility
- automatic feature learning
- human perception



Alex-Net, NIPS 2012

- flexibility
- automatic feature learning
- human perception



Alex-Net, NIPS 2012



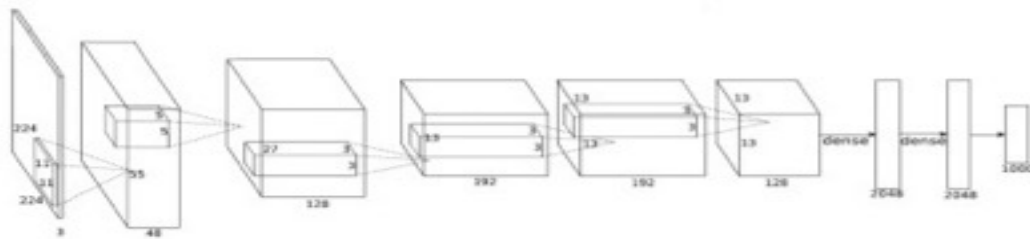
clarifai

Predicted Tags



call for

- flexibility
- automatic feature learning
- human perception



Alex-Net, NIPS 2012



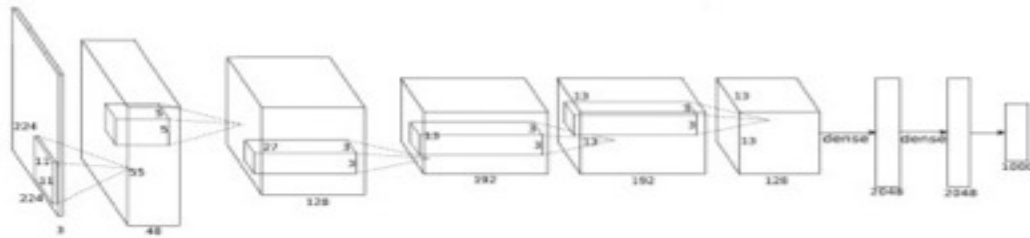
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Predicted Tags



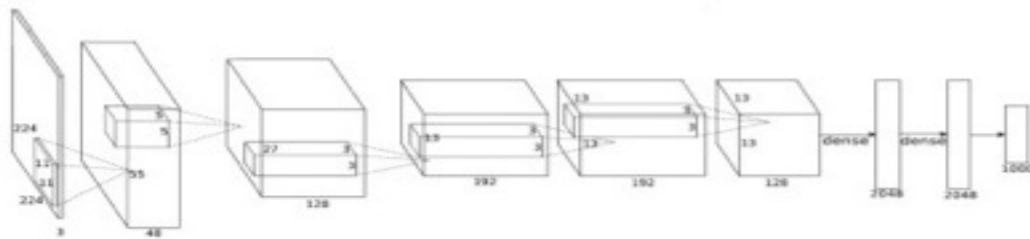
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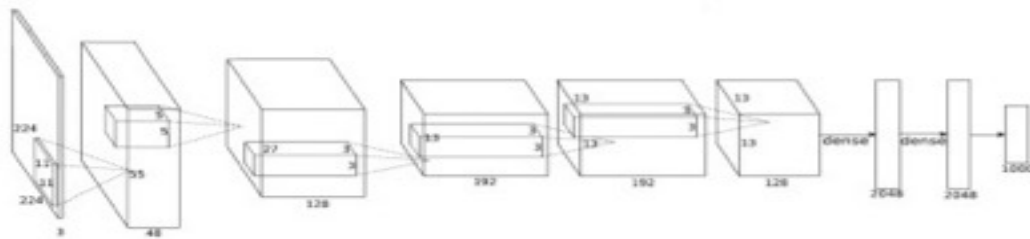
Alex-Net, NIPS 2012

- different categories
- different low-level features



Alex-Net, NIPS 2012

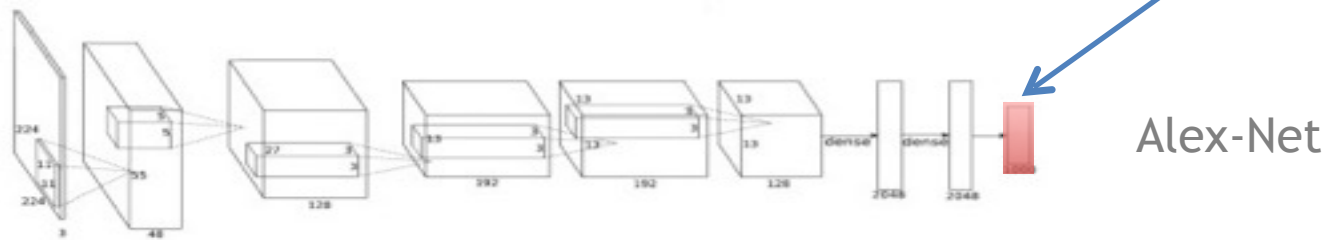
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- different low-level features



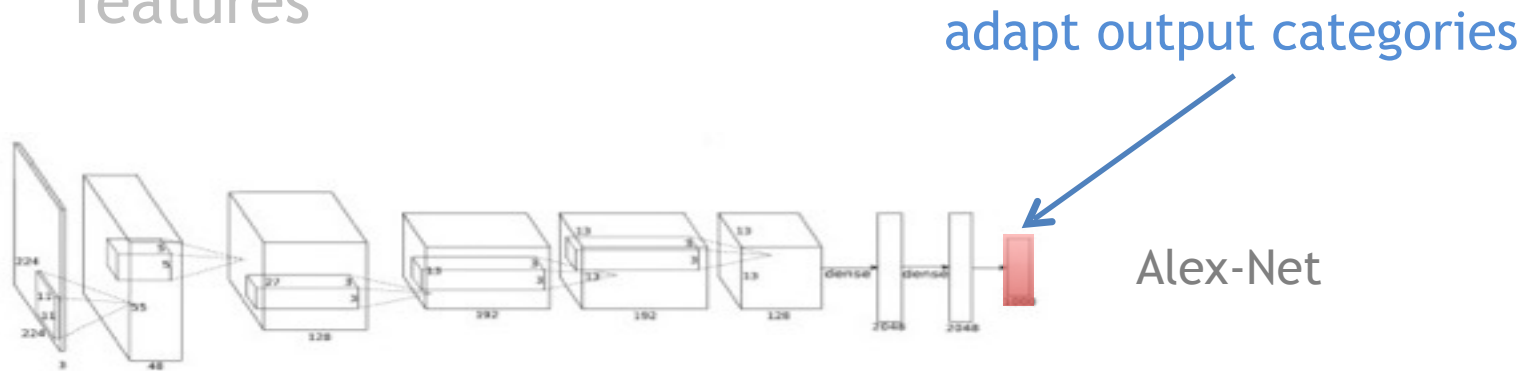
Alex-Net

- different categories
- different low-level features

adapt output categories

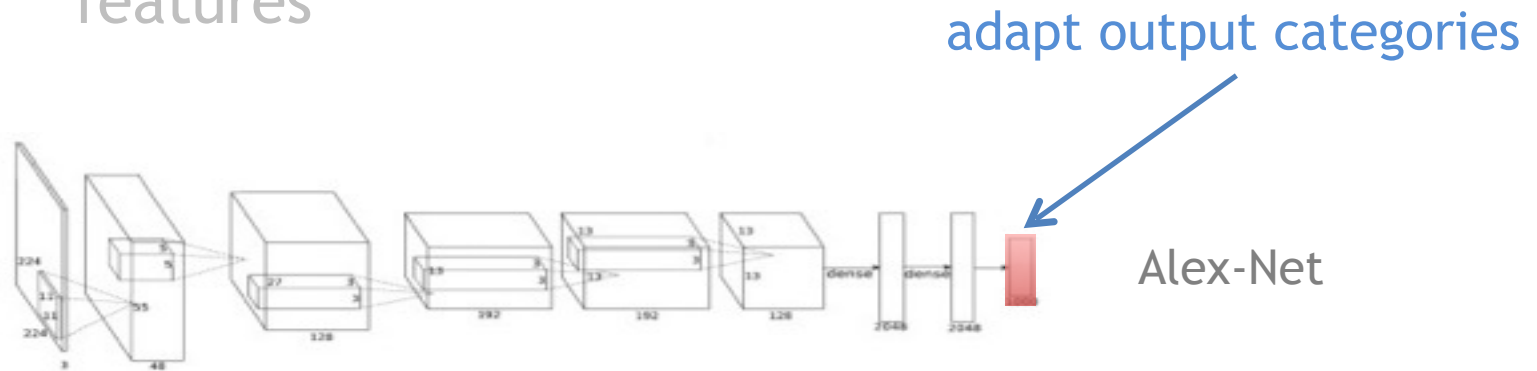


- different categories
- different low-level features



- Learning and transferring mid-level image representations
M Oquab et al, 2014

- different categories
- different low-level features

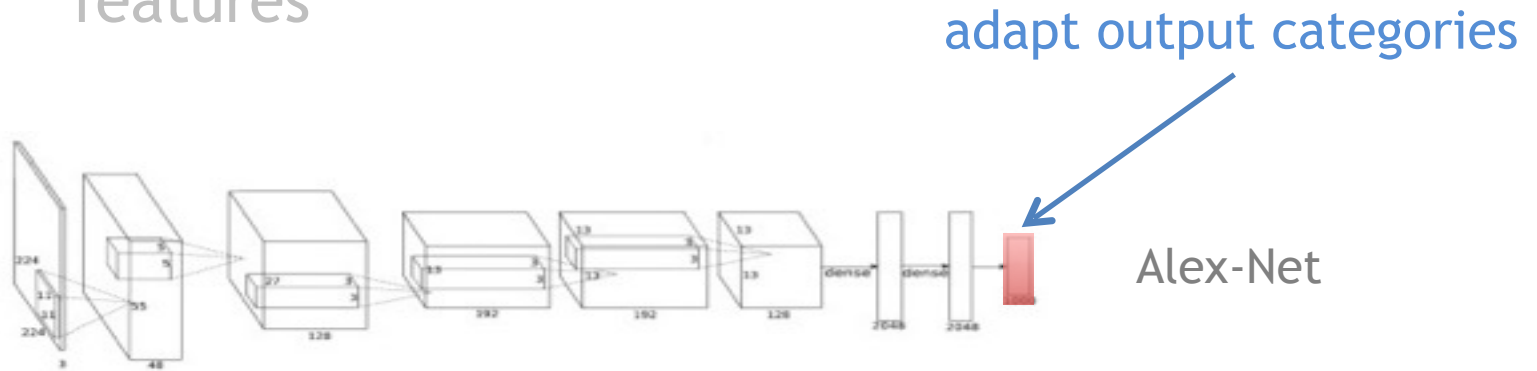


- Learning and transferring mid-level image representations

M Oquab et al, 2014



- different categories
- different low-level features



- Learning and transferring **mid-level** image representations

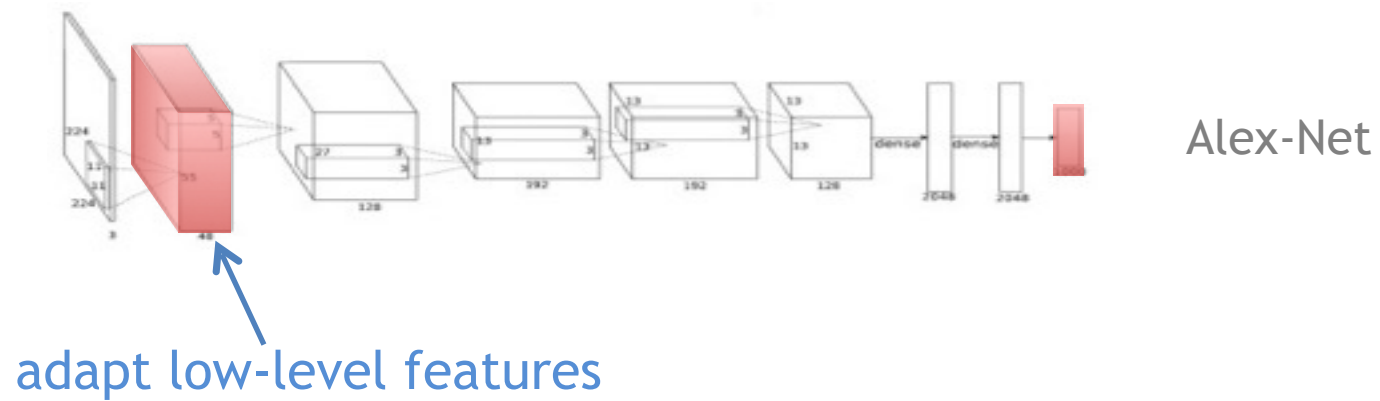
M Oquab et al, 2014

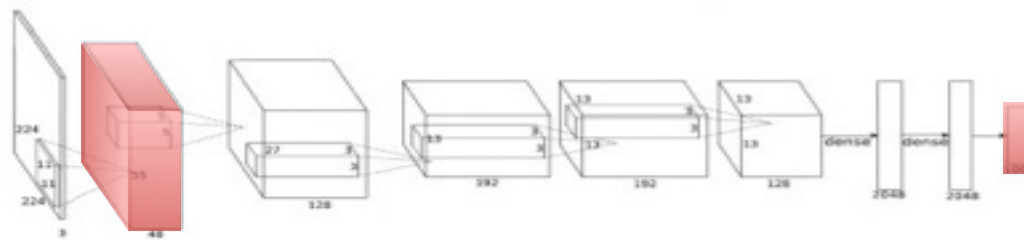


- different categories
- different low-level features



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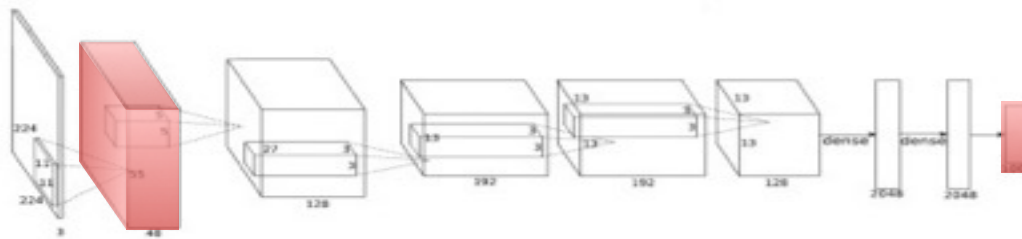




Alex-Net



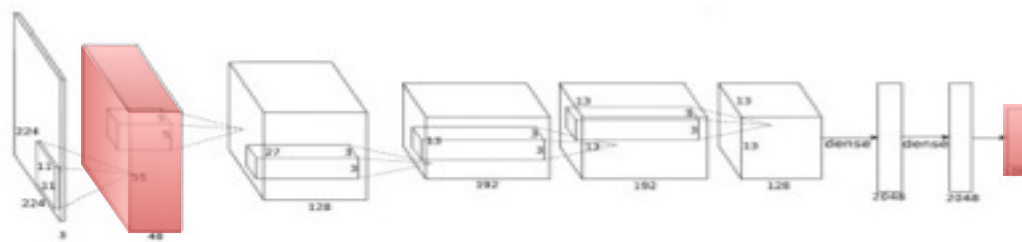
- 100 samples / category



Alex-Net



- 100 samples / category



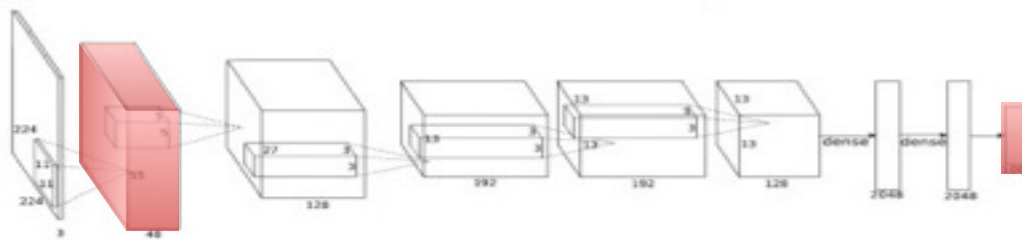
Alex-Net



- 1000 samples / category



- 100 samples / category



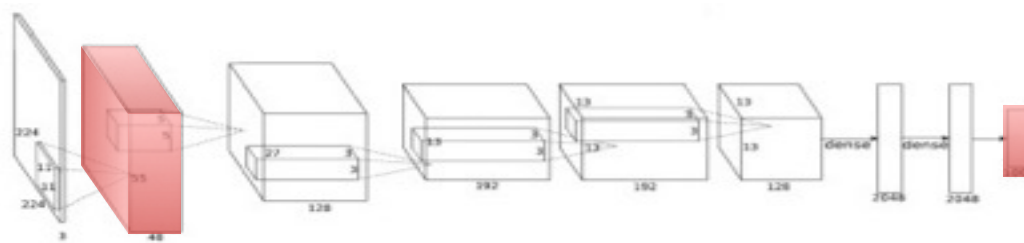
Alex-Net



- 1000 samples / category



- 100 samples / category



Alex-Net

train

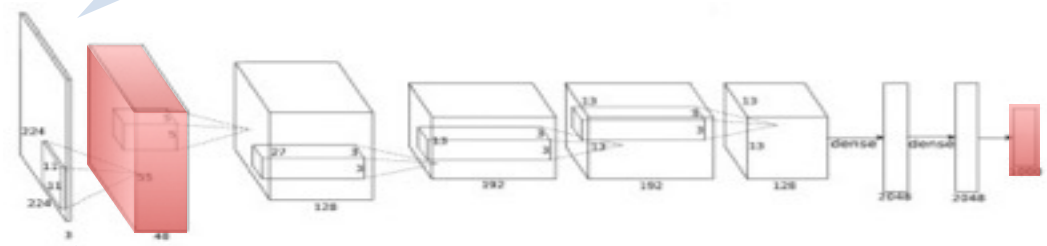


- 1000 samples / category



test

- 100 samples / category

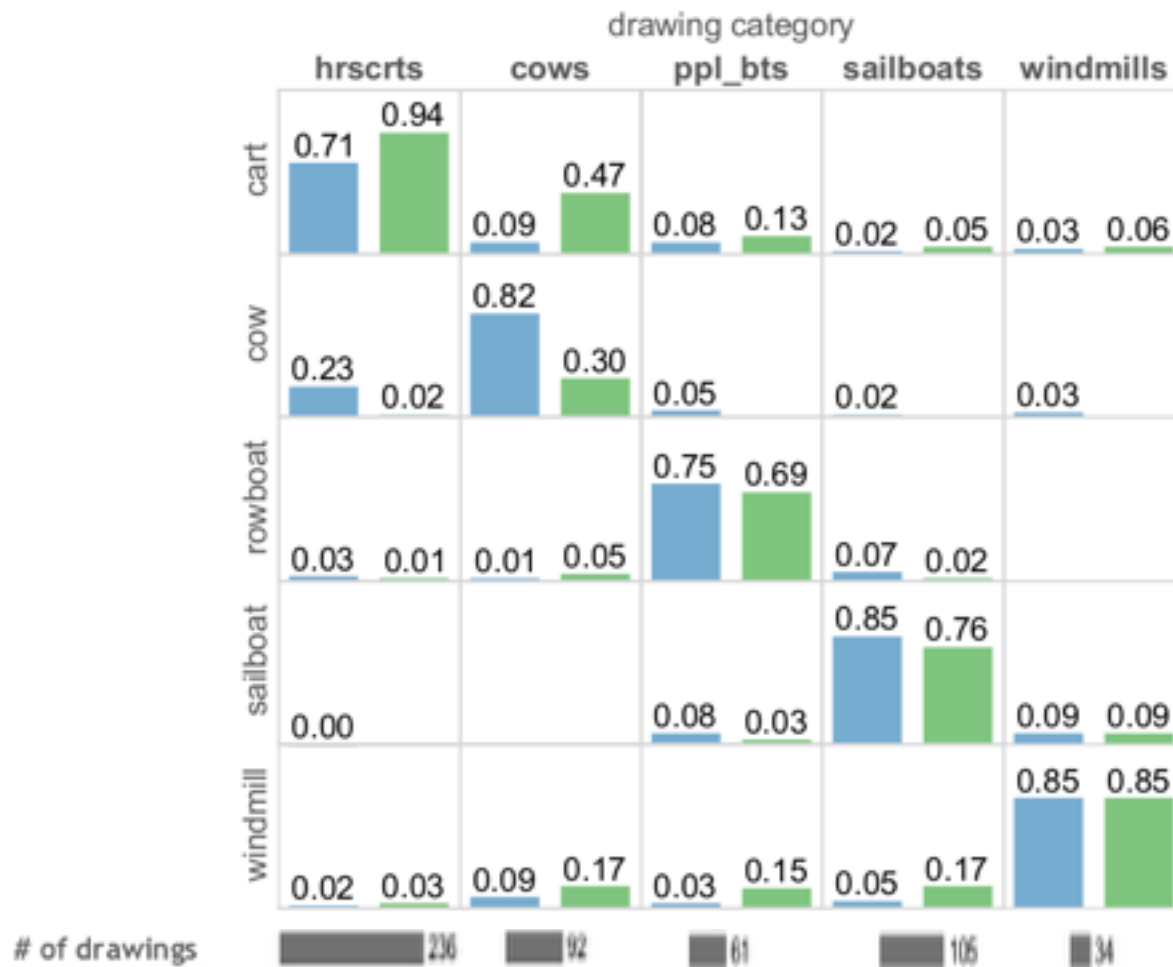
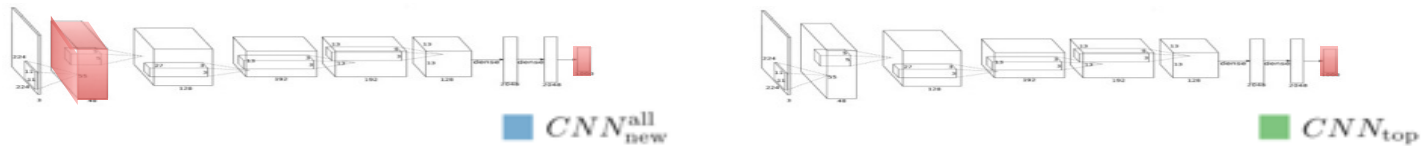


Alex-Net

train

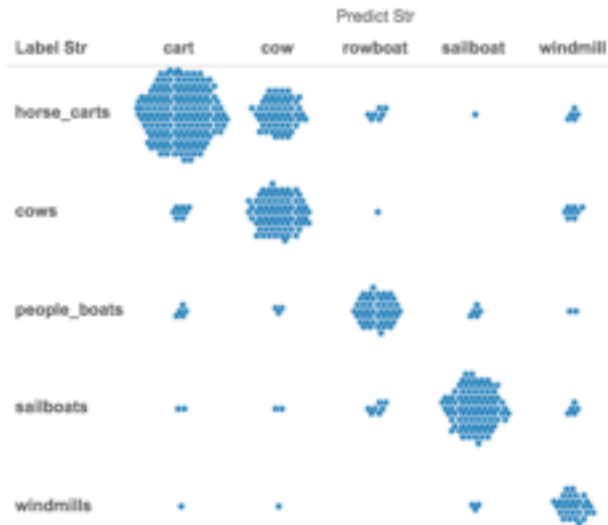


- 1000 samples / category



transfer learning

Drawing Recognition using CNN

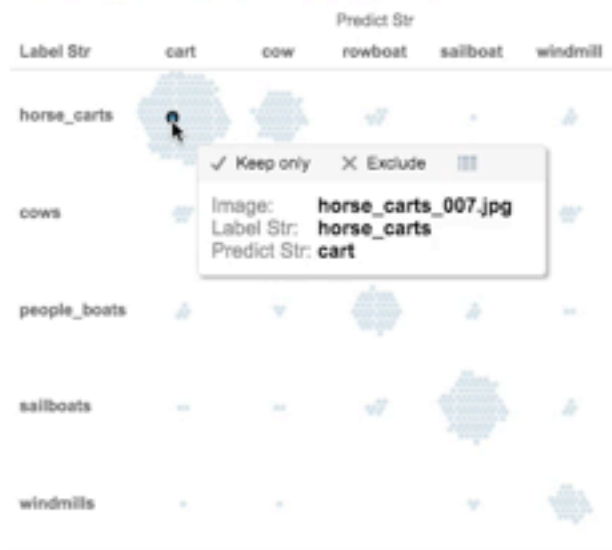


scatter plot of scores of horsecart drawings



| Label Str | Predict Str | | | | |
|--------------|-------------|-----|---------|----------|----------|
| | cart | cow | rowboat | sailboat | windmill |
| horse_carts | 168 | 55 | 7 | 1 | 5 |
| cows | 8 | 75 | 1 | | 8 |
| people_boats | 5 | 3 | 46 | 5 | 2 |
| sailboats | 2 | 2 | 7 | 89 | 5 |
| windmills | 1 | 1 | | 3 | 29 |

Drawing Recognition using CNN

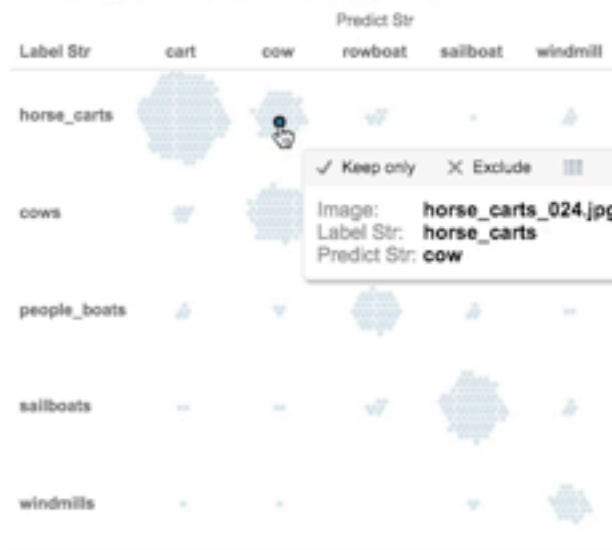


scatter plot of scores of horsecart drawings



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Drawing Recognition using CNN



scatter plot of scores of horsecart drawings



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