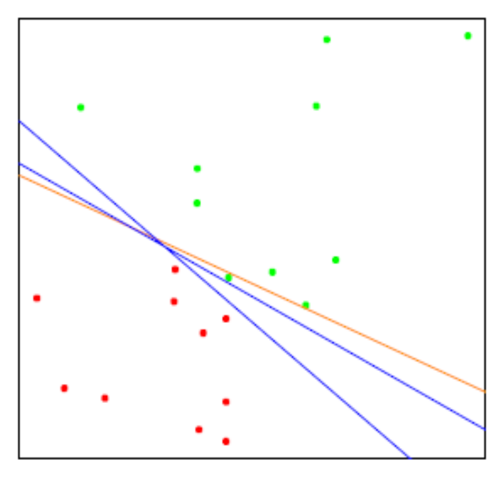


Deep Learning

Using a Convolutional Neural Network

Dr. – Ing. Morris Riedel

Adjunct Associated Professor

School of Engineering and Natural Sciences, University of Iceland

Research Group Leader, Juelich Supercomputing Centre, Germany

LECTURE 5

Transfer Learning

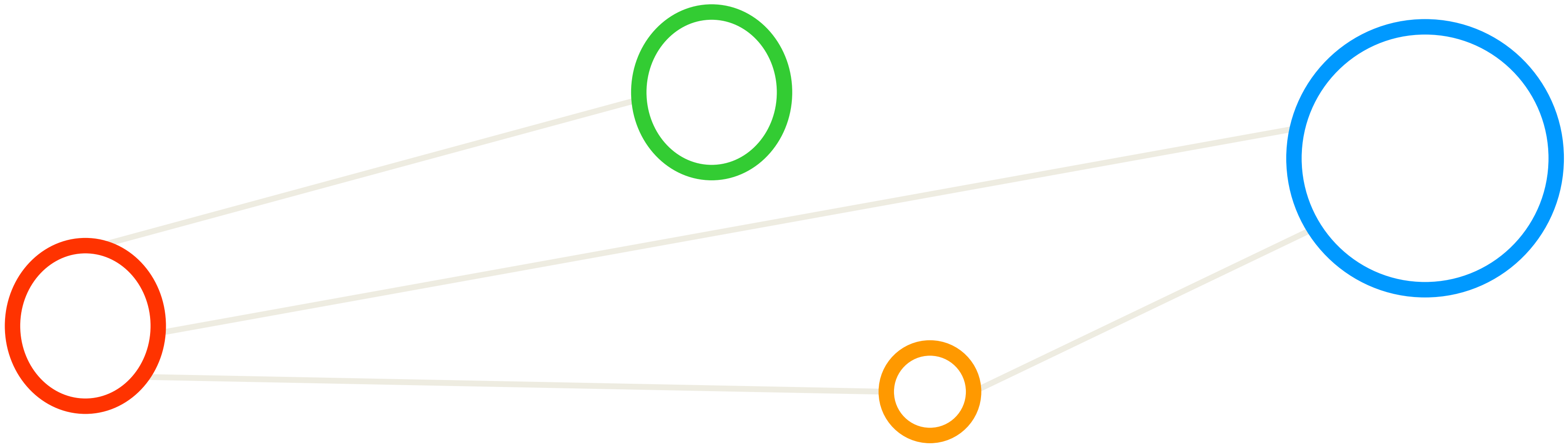
December 1st, 2017

Ghent, Belgium

UNIVERSITY OF ICELAND
SCHOOL OF ENGINEERING AND NATURAL SCIENCES
FACULTY OF INDUSTRIAL ENGINEERING,
MECHANICAL ENGINEERING AND COMPUTER SCIENCE

JÜLICH FORSCHUNGSZENTRUM

Outline



Outline of the Course

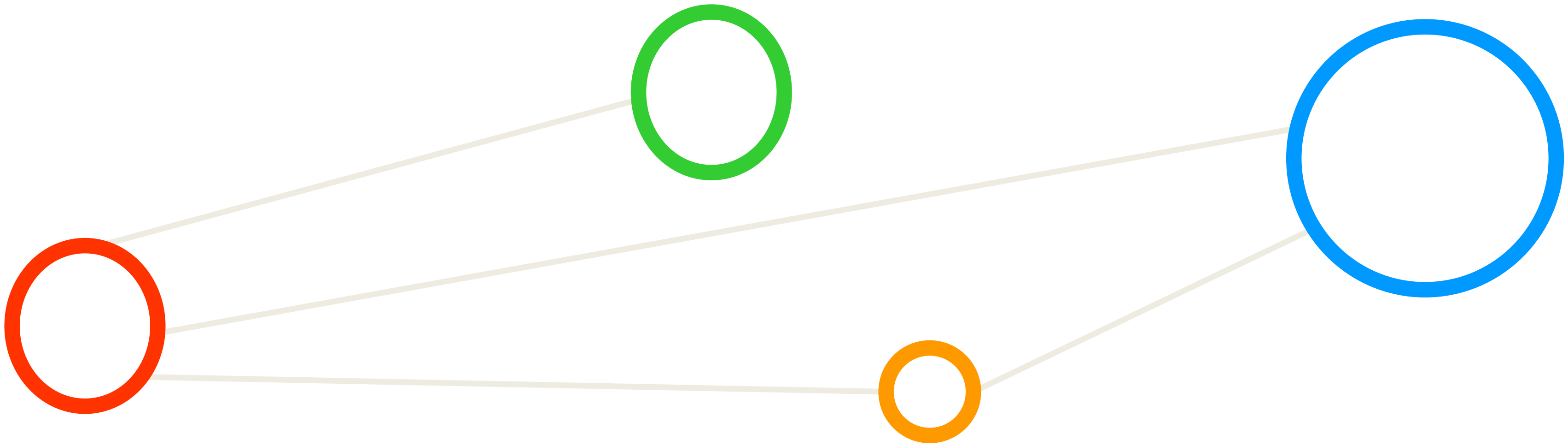
1. Deep Learning Fundamentals & GPGPUs
2. Convolutional Neural Networks & Tools
3. Convolutional Neural Network Applications
4. Convolutional Neural Network Challenges
5. Transfer Learning Technique
6. Other Deep Learning Models & Summary

Outline

- Transfer Learning Technique
  - Feature Learning Benefits & Motivation
  - Pre-Trained Models on ImageNet Dataset
  - Remote Sensing Data Application Example
  - Whole Scene vs. Pixel-wise Classification
  - Industry Example

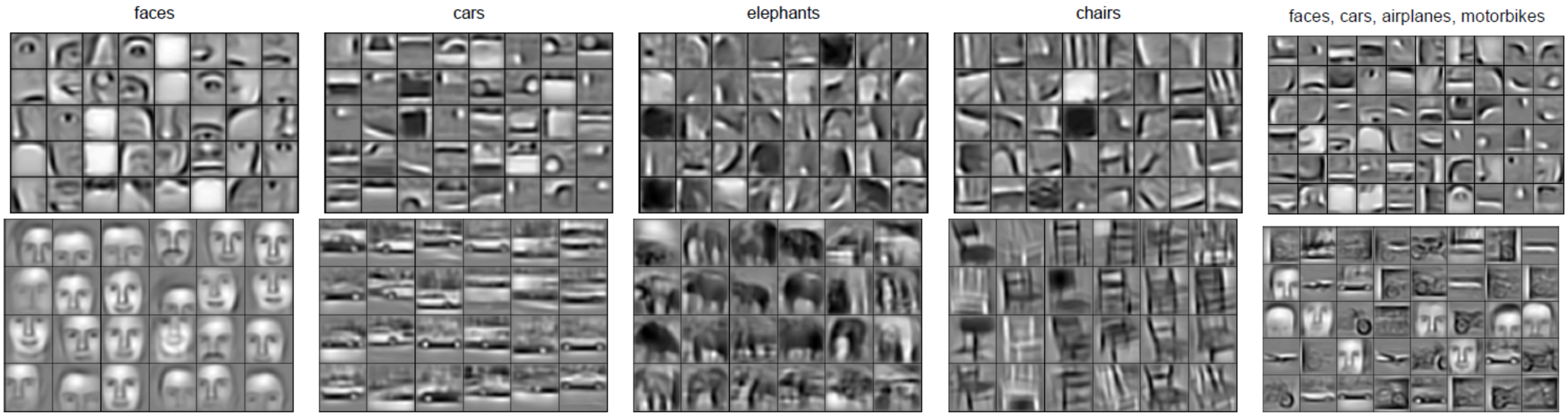
- Transfer Learning Applications
  - Medical Datasets
  - X-Ray Security Screening Images
  - Media Dataset PASCAL
  - Tool Support
  - Summary Transfer Learning

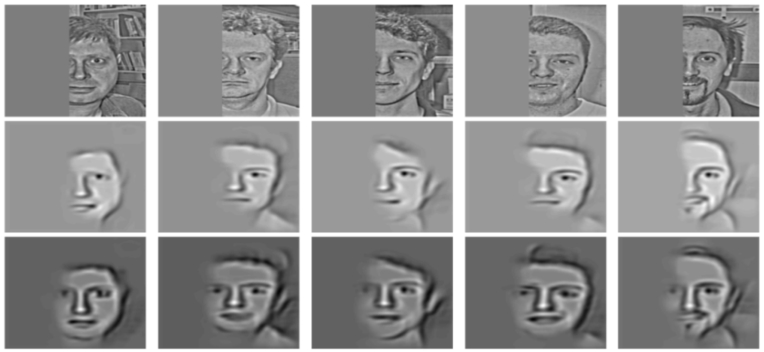
Transfer Learning Technique



Exercises – Group Assignment – Check Status

Deep Learning – Feature Learning Benefits – Revisited



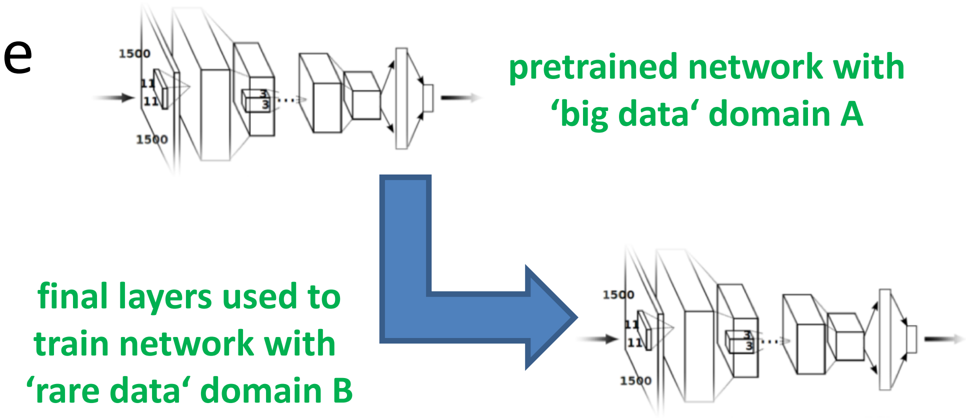


[1] H. Lee et al., 'Convolutional Deep Belief Networks for Scalable Unsupervised Learning of Hierarchical Representations'

- **Traditional machine learning applied feature engineering before modeling**
- **Feature engineering requires expert knowledge, is time-consuming and a often long manual process, requires often 90% of the time in applications, and is sometimes even problem-specific**
- **Deep Learning enables feature learning promising a massive time advancement**

Transfer Learning – Motivation

- Rare Data Application Example
  - Indian Pines Dataset
  - Extremely less data to train a deep learning network
  - Common in remote sensing and other engineering or academic discplines
  - Massively risk in overfitting the data due to less available training data with labels
  - Complexity: pixel-wise classification vs. whole scene
  - Too costly to acquire high quality labels (e.g. groundtruth compaigns)

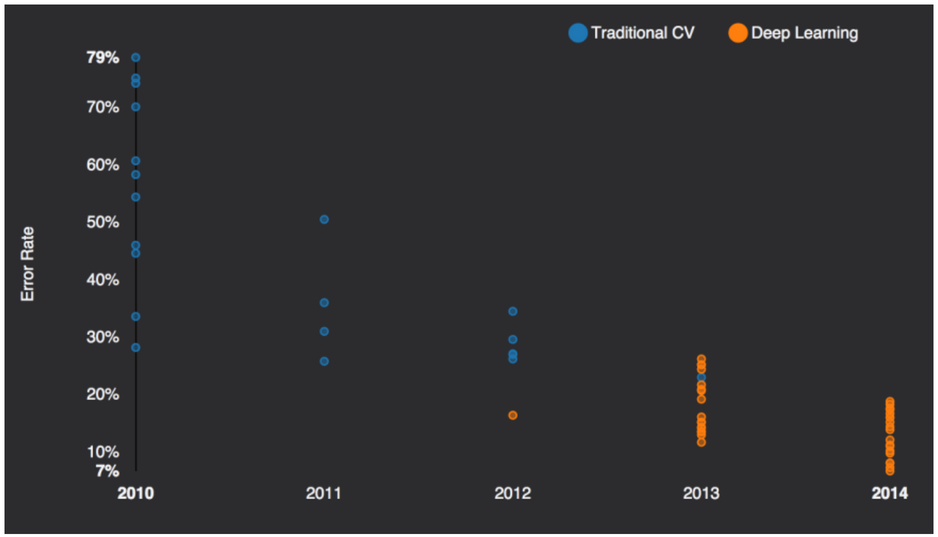


- **Representations from very deep networks are generic and can facilitate transfer learning between different application domains**
- **Representation contained in the last layers of deep pretrained networks is of major influence in classification accuracy**
- **Earlier – the more shallow – layers insignificantly affect the classification outcome**

[2] J. Donahue et al., “Decaf: A deep convolutional activation feature for generic visual recognition,”

Basic ImageNet Dataset as Base for Learning – Revisited

- Dataset: ImageNet
  - Total number of images: 14.197.122
  - Number of images with bounding box annotations: 1.034.908

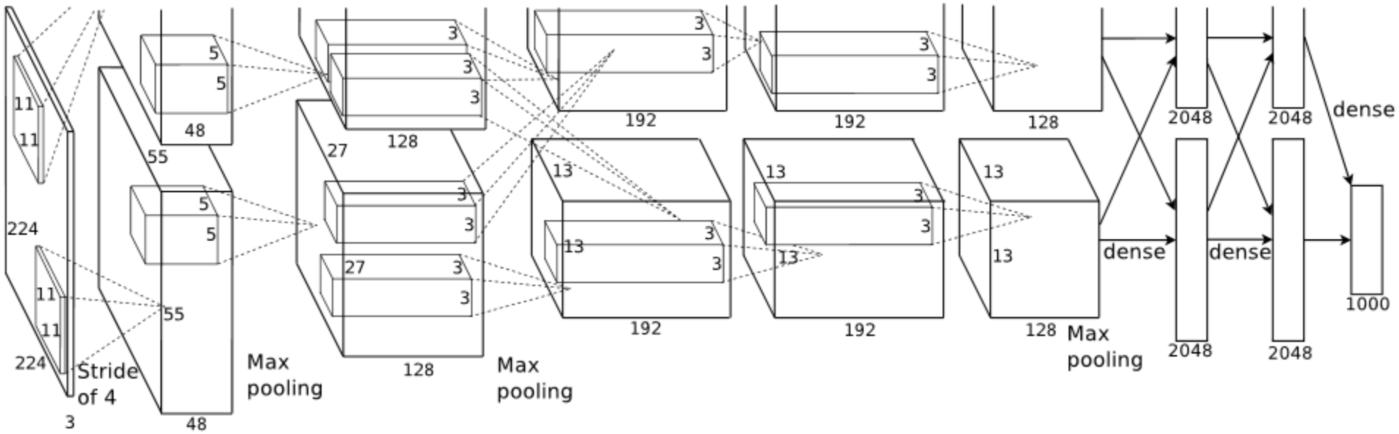


[3] J. Dean et al., 'Large-Scale Deep Learning'

High level category	# synset (subcategories)	Avg # images per synset	Total # images
amphibian	94	591	56K
animal	3822	732	2799K
appliance	51	1164	59K
bird	856	949	812K
covering	946	819	774K
device	2385	675	1610K
fabric	262	690	181K
fish	566	494	280K
flower	462	735	339K
food	1495	670	1001K
fruit	309	607	188K
fungus	303	453	137K
furniture	187	1043	195K
geological formation	151	838	127K
invertebrate	728	573	417K
mammal	1138	821	934K
musical instrument	157	891	140K
plant	1666	600	999K
reptile	268	707	190K
sport	166	1207	200K
structure	1239	763	946K
tool	316	551	174K
tree	993	568	564K
utensil	86	912	78K
vegetable	176	764	135K
vehicle	481	778	374K
person	2035	468	952K

[4] ImageNet Web page

AlexNet & Overfeat Pre-Trained ImageNet Networks



[15] AlexNet

Layer	1	2	3	4	5	6	7	Output 8
Stage	conv + max	conv + max	conv	conv	conv + max	full	full	full
# channels	96	256	512	1024	1024	3072	4096	1000
Filter size	11x11	5x5	3x3	3x3	3x3	-	-	-
Conv. stride	4x4	1x1	1x1	1x1	1x1	-	-	-
Pooling size	2x2	2x2	-	-	2x2	-	-	-
Pooling stride	2x2	2x2	-	-	2x2	-	-	-
Zero-Padding size	-	-	1x1x1x1	1x1x1x1	1x1x1x1	-	-	-
Spatial input size	231x231	24x24	12x12	12x12	12x12	6x6	1x1	1x1

[14] Overfeat on Github

[6] P. Sermanet et al., 'OverFeat: Integrated Recognition, Localization and Detection using Convolutional Networks'

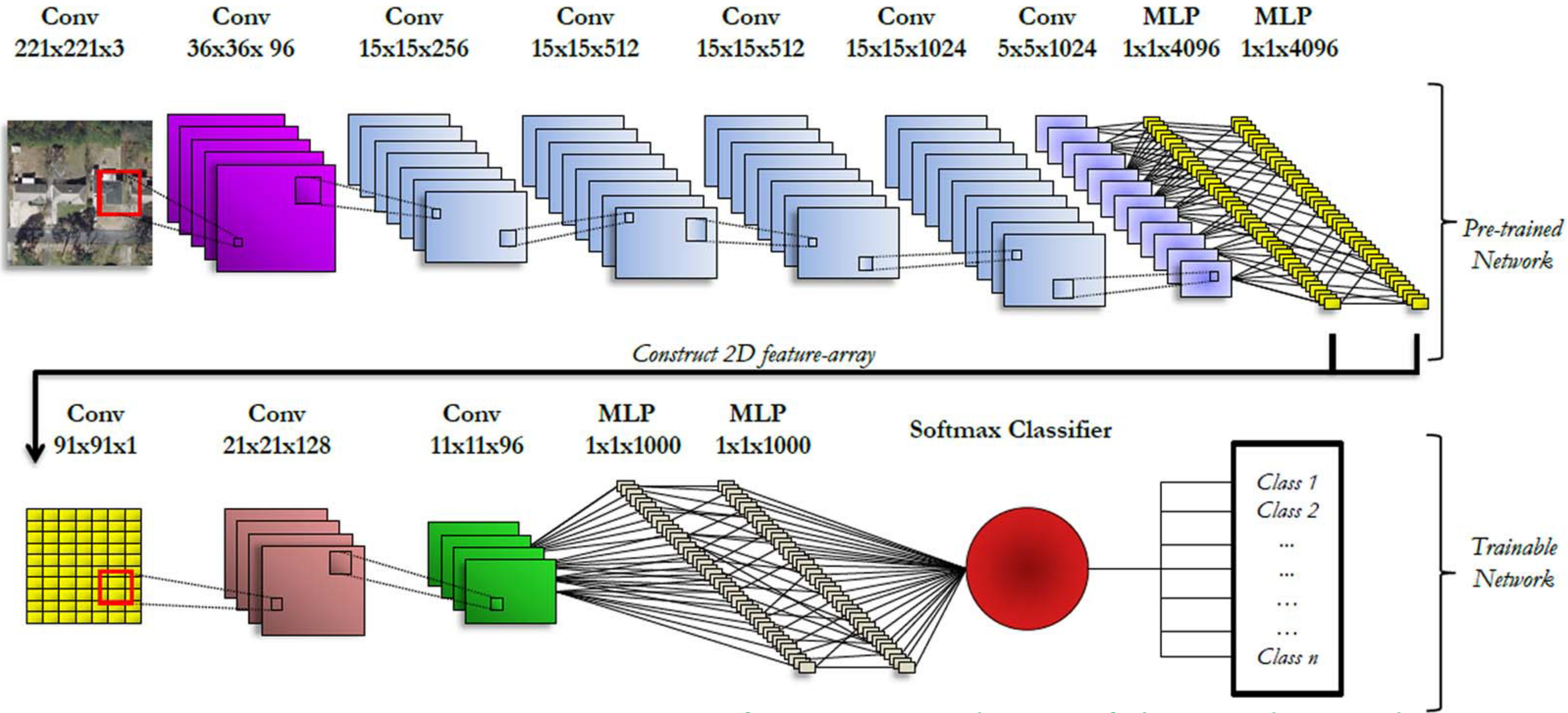
Remote Sensing Dataset – UC Merced Land

- Metadata
  - Consists of 21 land use and land cover classes
  - Each class has 100 images and the contained images measure 256x256 pixels
  - Spatial resolution of about 30 cm per pixel
  - All images are in the RGB color space
  - Extracted from the USGS National Map Urban Area Imagery collection, i.e. the underlying images were acquired from an aircraft
  - Drawback: dataset with 100 images per class is very small-scale

[13] UC Merced Land Remote Sensing Dataset

CNN Architecture – Using a Pre-Trained Networks

Using available Overfeat as pre-trained network



Overfeat is an improved version of AlexNet and is trained on 1.2 million labeled images from ImageNet

[5] D. Marmanis et al., 'Deep Learning Earth Obervation Classification Using ImageNet Pretrained Networks', 2016

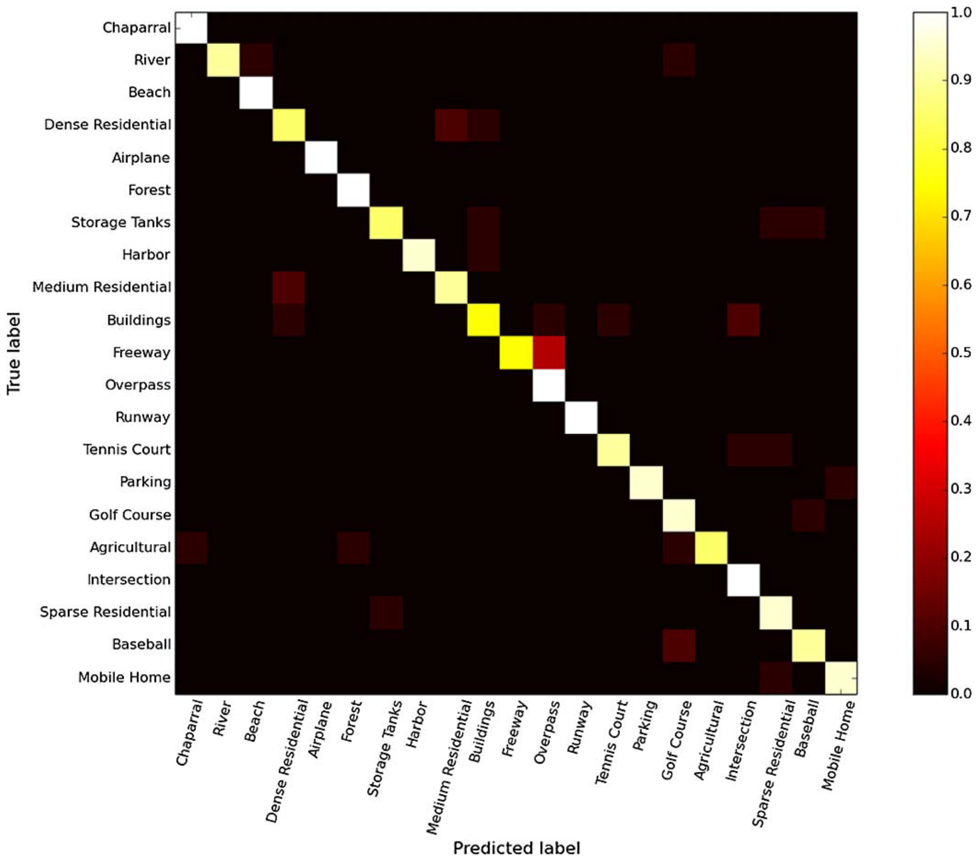
[6] P. Sermanet et al., 'OverFeat: Integrated Recognition, Localization and Detection using Convolutional Networks'

Selected Evaluations vs. Traditional Classifiers

Method & Algorithm	Test-set Accuracy
Random Forest with RGB feature	44%
CNN with RGB feature	44.5%
Random Forest with Overfeat features	86.9%
CNN with Overfeat feature	**92.4 %**

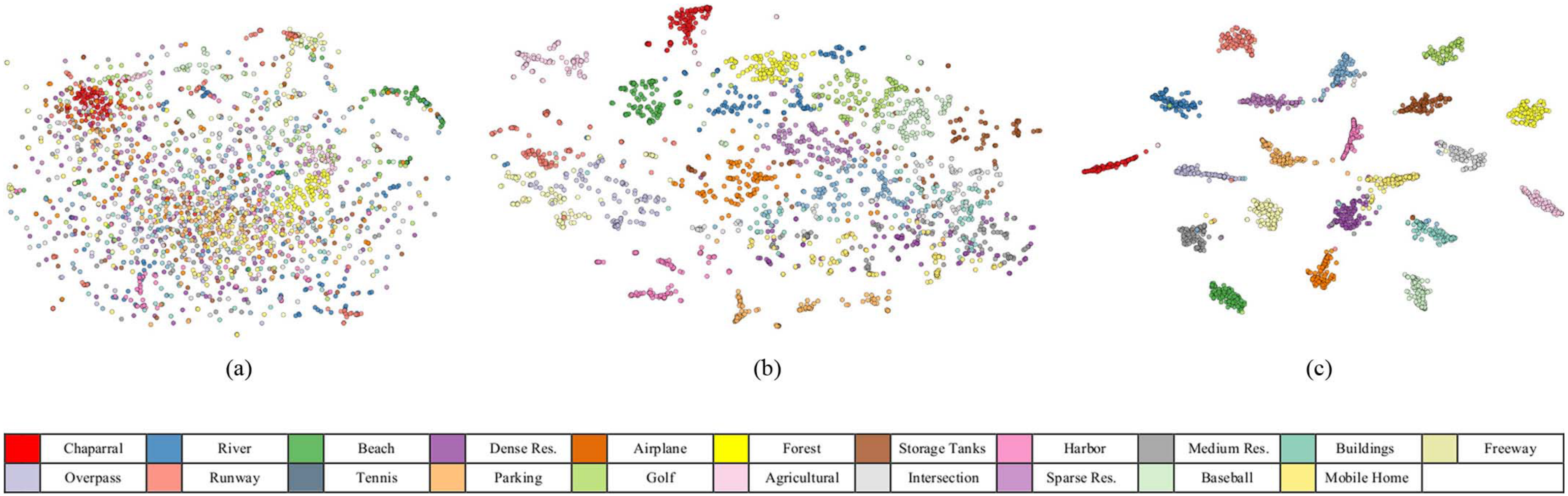
UC Merced Land Dataset

Method & Algorithm	Test-set Accuracy
BOVW [2]	71.8%
SPMK [1]	74%
SPCK++ [2]	76%
Sparce Coding [4]	81.7%
Salient Unsupervised Learning [6]	82.8% $\pm$ 1.18%
MinTree + KD-Tree [3]	83.1% $\pm$ 1.2%
CNN with Overfeat feature	**92.4 %**



[5] D. Marmanis et al., 'Deep Learning Earth Obervation Classification Using ImageNet Pretrained Networks', 2016

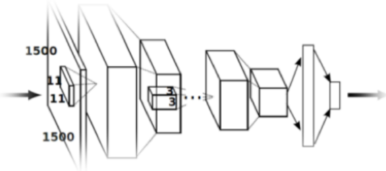
Transfer Learning Results – Support Classifier



[5] D. Marmanis et al., 'Deep Learning Earth Obervation Classification Using ImageNet Pretrained Networks', 2016

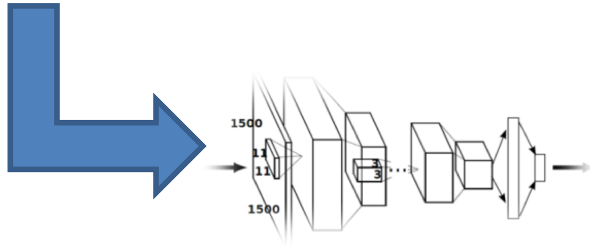
- **Learned features in (b) already help the classifier to distinguish classes**

Transfer Learning Results – Transferability



pretrained network with
'big data' domain A

final layers used to
train network with
'rare data' domin B



- Data randomly taken from various city images and used with the trained CNN using pre-trained ImageNet
- Even on unseen data from complete different datasets transfer learning is working well
- Shown for scene-wide classification, not much for pixel-wise classification

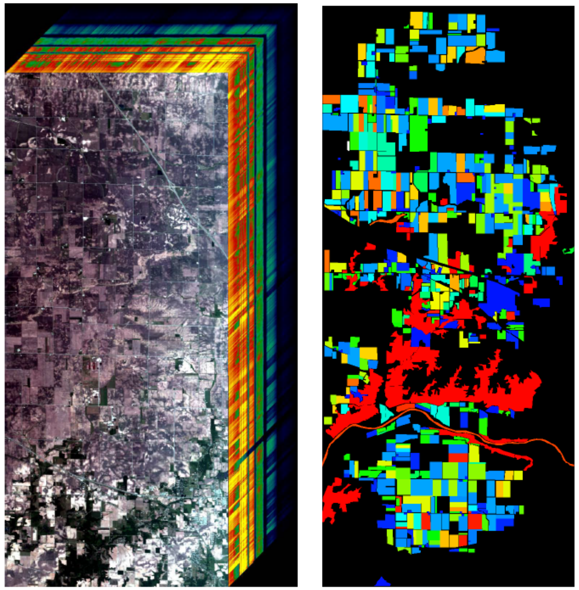
[5] D. Marmanis et al., 'Deep Learning Earth Obervation Classification Using ImageNet Pretrained Networks', 2016

Deep Learning – Selected Challenges – Revisited

- Pixel-wise is different then the whole scene → more work!

Class		Number of samples		Class		Number of samples	
Number	Name	Training	Test	Number	Name	Training	Test
1	Buildings	1720	15 475	27	Pasture	1039	9347
2	Corn	1778	16 005	28	pond	10	92
3	Corn?	16	142	29	Soybeans	939	8452
4	Corn-EW	51	463	30	Soybeans?	89	805
5	Corn-NS	236	2120	31	Soybeans-NS	111	999
6	Corn-CleanTill	1240	11 164	32	Soybeans-CleanTill	507	4567
7	Corn-CleanTill-EW	2649	23 837	33	Soybeans-CleanTill?	273	2453
8	Corn-CleanTill-NS	3968	35 710	34	Soybeans-CleanTill-EW	1180	10 622
9	Corn-CleanTill-NS-Irrigated	80	720	35	Soybeans-CleanTill-NS	1039	9348
10	Corn-CleanTilled-NS?	173	1555	36	Soybeans-CleanTill-Drilled	224	2018
11	Corn-MinTill	105	944	37	Soybeans-CleanTill-Weedy	54	489
12	Corn-MinTill-EW	563	5066	38	Soybeans-Drilled	1512	13 606
13	Corn-MinTill-NS	886	7976	39	Soybeans-MinTill	267	2400
14	Corn-NoTill	438	3943	40	Soybeans-MinTill-EW	183	1649
15	Corn-NoTill-EW	121	1085	41	Soybeans-MinTill-Drilled	810	7288
16	Corn-NoTill-NS	569	5116	42	Soybeans-MinTill-NS	495	4458
17	Fescue	11	103	43	Soybeans-NoTill	216	1941
18	Grass	115	1032	44	Soybeans-NoTill-EW	253	2280
19	Grass/Trees	233	2098	45	Soybeans-NoTill-NS	93	836
20	Hay	113	1015	46	Soybeans-NoTill-Drilled	873	7858
21	Hay?	219	1966	47	Swampy Area	58	525
22	Hay-Alfalfa	226	2032	48	River	311	2799
23	Lake	22	202	49	Trees?	58	522
24	NotCropped	194	1746	50	Wheat	498	4481
25	Oats	174	1568	51	Woods	6356	57 206
26	Oats?	34	301	52	Woods?	14	130

remote sensing cube & ground reference



- **Example: Fully connected Artificial Neural Network (ANN) achieved around 20% w/o feature engineering**
- **CNN architecture required some work (e.g. Tensors)**
- **Transfer Learning a good option, but more feature work**

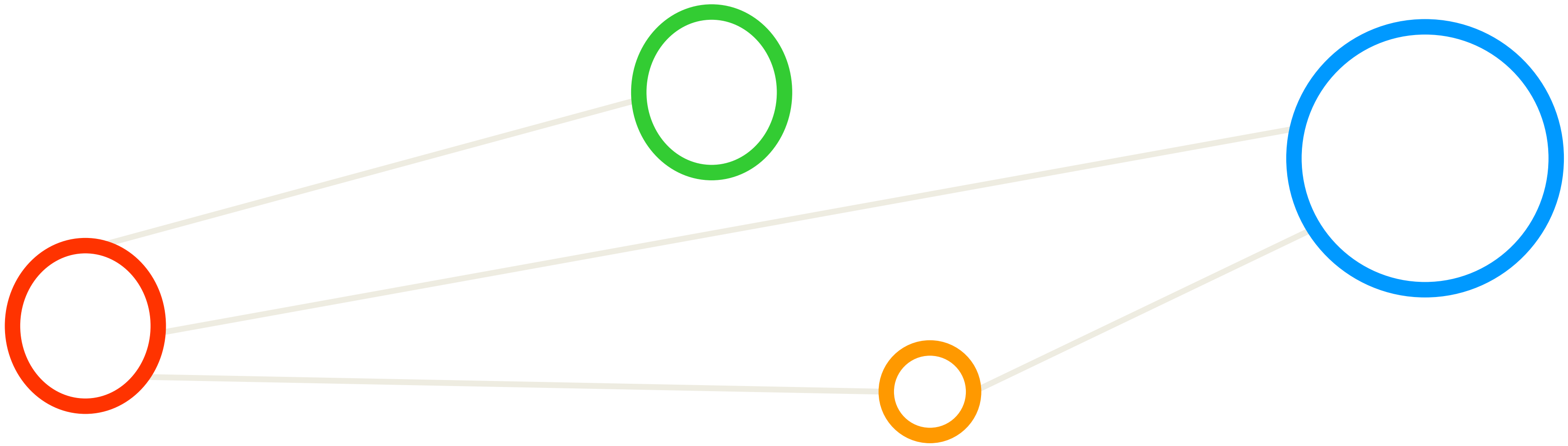
[7] G. Cavallaro, M. Riedel, J.A. Benediktsson et al., Journal of Selected Topics in Applied Earth Observation and Remote Sensing, 2015

Exercises – Group Assignment – Check Status

[Video] Transfer Learning in Industry – Part One

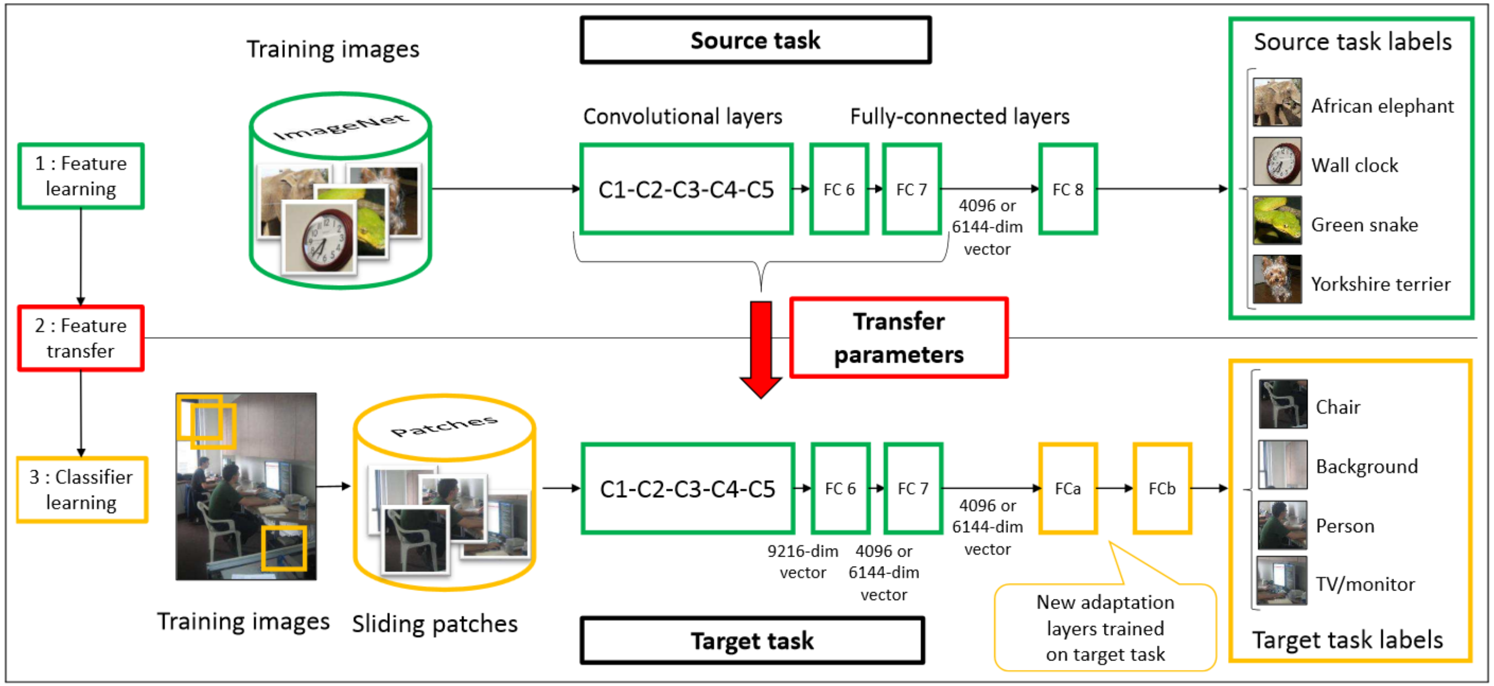
[11] Transfer Learning – Part One, YouTube

Transfer Learning in Other Domains



Media: PASCAL Visual Object Classes Dataset

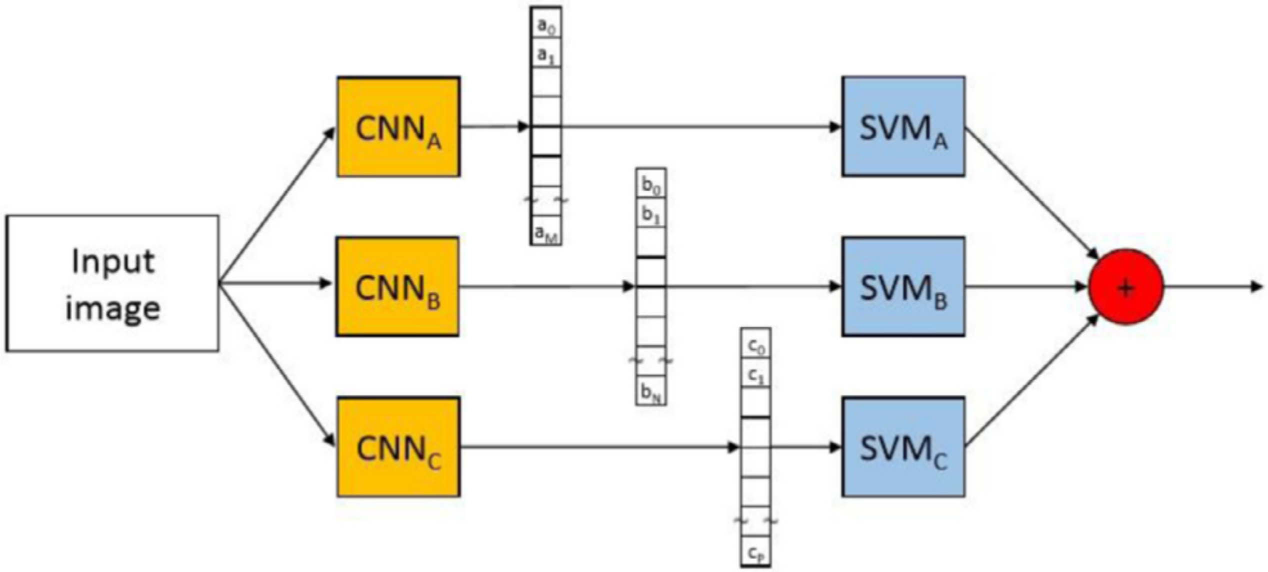
- Media images
  - Pre-trained on ImageNet with good results (source task)
  - Pre-trained parameters of the internal layers (aka learned features) of the network (C1-FC7) are then transferred to the target tasks



[10] M. Oquab et al., 'Learning and Transferring Mid-Level Image Representations Using Convolutional Neural Networks', 2014

Medical Image Datasets

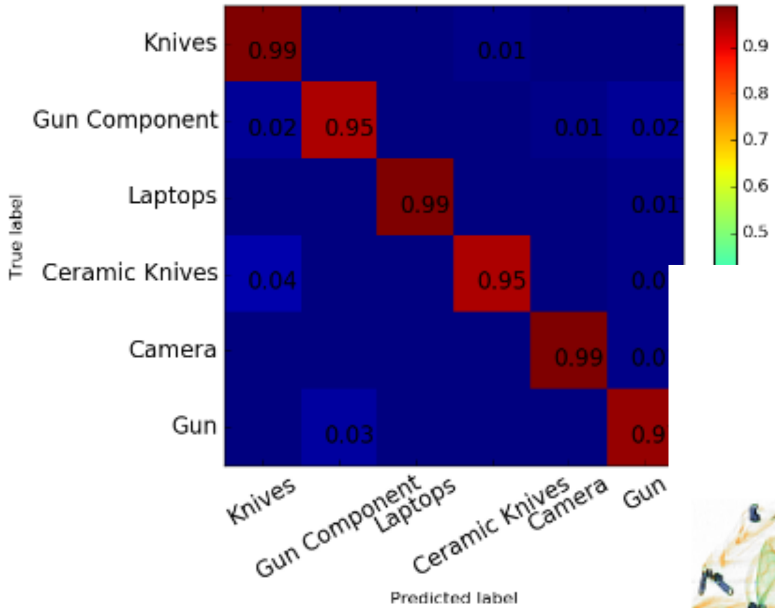
- Science: Medical image datasets
  - Use pre-trained CNN features as input for SVM classifier



[8] L. Nanni et al.'How Could a Subcellular Image, or a Painting by Van Gogh, Be Similar to a Great White Shark or to a Pizza?', Pattern Recognit. Lett. 2017

Society: X-Ray Security Screening Images

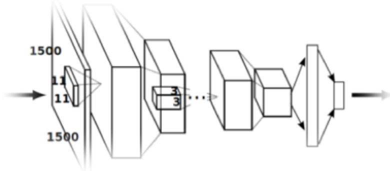
- Civil Security
  - Different types of pre-trained networks used



	TP%	TN%	FP%	FN%	PRE	REC	ACC
$AlexNet_{1-8}$	97.56	99.31	0.68	2.43	0.98	0.98	**0.99**
$AlexNet_{2-8}$	98.53	97.60	2.40	1.47	0.83	**0.99**	0.98
$AlexNet_{3-8}$	**98.62**	**99.79**	**0.21**	**1.38**	**0.99**	**0.99**	**0.99**
$AlexNet_{4-8}$	97.62	98.79	1.21	**1.38**	**0.99**	0.98	0.98
$AlexNet_{5-8}$	97.47	99.72	0.28	2.53	**0.99**	0.97	0.98
$AlexNet_{6-8}$	96.21	99.27	0.73	3.79	0.98	0.96	**0.99**
$AlexNet_{7-8}$	94.49	96.35	3.65	5.51	0.75	0.94	0.96
$AlexNet_{7-8}$	95.64	99.07	0.93	4.36	0.97	0.96	0.98
$AlexNet_{8}$	93.58	97.96	2.03	6.42	0.93	0.94	0.97
$SURF + RF$	94.10	65.44	34.56	5.90	0.90	0.94	0.87
$SURF + SVM$ [6]	97.43	85.07	14.93	2.57	0.96	0.97	0.95

[9] S. Akçay et al., 'Transfer Learning using Convolutional Neural Networks for Object Classification within X-ray Baggage Security Imagery, 2016

Transfer Learning Summary



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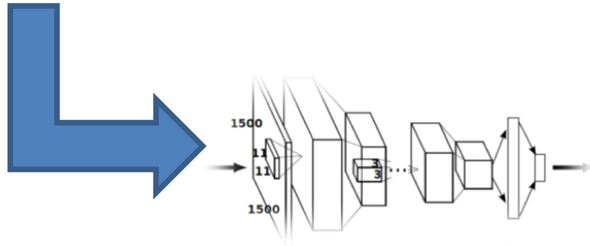


- Key Messages
  - Unique possibilities for certain scientific areas with a lack of labels
  - Good for relatively 'simple' datasets (whole scence classification)
  - Quite challenging for 'tough' datasets (e.g. pixel-wise classification)
- Tool Support
  - Existing pre-trained networks can be easily downloaded (e.g. AlexNet or Overfeat)
  - Extraxtion of features possible to be subsequently used in deep learning frameworks (e.g. Keras, Tensorflow, etc.)

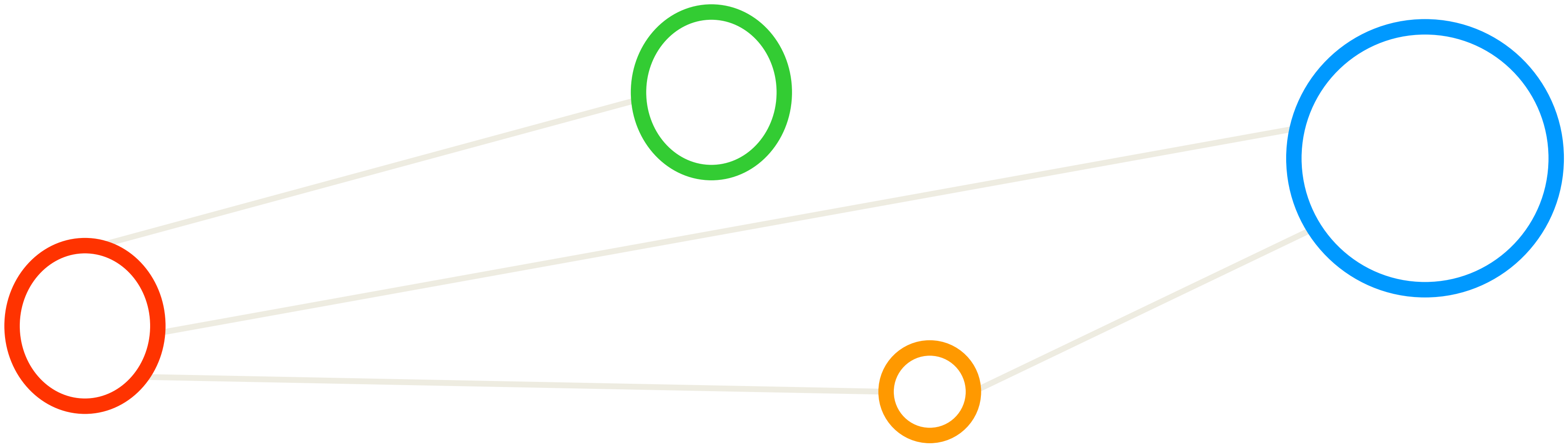
- **Studies reveal transferability of different layers in deep CNNs pretrained with ImageNet**
- **Transfer learning is relevant for all sciences & worth studying when lack of labels exist**

Exercises – Group Assignment – Check Status

[Video] Transfer Learning in Industry – Part Two

[12] Transfer Learning – Part One, YouTube

Lecture Bibliography



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- [1] H. Lee et al., ‘Convolutional Deep Belief Networks for Scalable Unsupervised Learning of Hierarchical Representations’, Proceedings of the 26th annual International Conference on Machine Learning (ICML), 2009
- [2] J. Donahue *et al.*, “Decaf: A deep convolutional activation feature for generic visual recognition,” unpublished paper, 2013,
  Online: http://arxiv.org/abs/1310.1531
- [3] J. Dean et al., ‘Large scale deep learning’, Keynote GPU Technical Conference, 2015
- [4] ImageNet Web page,
  Online: http://image-net.org
- [5] Dimitrios Marmanis et al., ‘Deep Learning Earth Obervation Classification Using ImageNet Pretrained Networks‘, IEEE Geoscience and Remote Sensing Letters, Volume 13 (1), 2016,
  Online: http://ieeexplore.ieee.org/document/7342907/
- [6] P. Sermanet et al., ‘OverFeat: Integrated Recognition, Localization and Detection using Convolutional Networks’, Online: http://arxiv.org/abs/1312.6229
- [7] G. Cavallaro, M. Riedel, J.A. Benediktsson et al., ‘On Understanding Big Data Impacts in Remotely Sensed Image Classification using Support Vector Machine Methods’, IEEE Journal of Selected Topics in Applied Earth Observation and Remote Sensing, 2015, DOI: 10.1109/JSTARS.2015.2458855
- [8] Nanni, L.; Ghidoni, S. How Could a Subcellular Image, or a Painting by Van Gogh, Be Similar to a Great White Shark or to a Pizza? Pattern Recognit. Lett. 2017, 85, 1–7.
- [9] Akçay, S.; Kundegorski, M.E.; Devereux, M.; Breckon, T.P. Transfer Learning using Convolutional Neural Networks for Object Classification within X-ray Baggage Security Imagery. In Proceedings of the 2016 IEEE International Conference on Image Processing (ICIP), Phoenix, AZ, USA, 25–28 September 2016; pp. 1057–1061.

Lecture Bibliography (2)

- [10] Oquab, M.; Bottou, L.; Laptev, I.; Sivic, J. Learning and Transferring Mid-Level Image Representations Using Convolutional Neural Networks. In Proceedings of the 2014 IEEE Conference on Computer Vision and Pattern Recognition, Columbus, OH, USA, 23–28 June 2014; pp. 1717–1724.
- [11] YouTube Video, 'Transfer Learning with indico - Ep. 27 Part 1 (Deep Learning SIMPLIFIED)', Online: https://www.youtube.com/watch?v=Yx6Wv_SCKjI
- [12] YouTube Video, ''Fashion Matching Demo with indico - Ep. 27 Part 2 (Deep Learning SIMPLIFIED), Online: https://www.youtube.com/watch?v=Ikg1xNdabFo
- [13] UC Merced Land Use Remote Sensing Dataset, Online: http://weegee.vision.ucmerced.edu/datasets/landuse.html
- [14] Overfeat on Github, Online: https://github.com/sermanet/OverFeat
- [15] AlexNet, Online: https://www.nvidia.cn/content/tesla/pdf/machine-learning/imagenet-classification-with-deep-convolutional-nn.pdf


services
measurement
within
fusion
new
funding
Policy-based
concepts
device
Analysis
forms
cross-disciplinary
resources
Centre
climate
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