Transfer Learning

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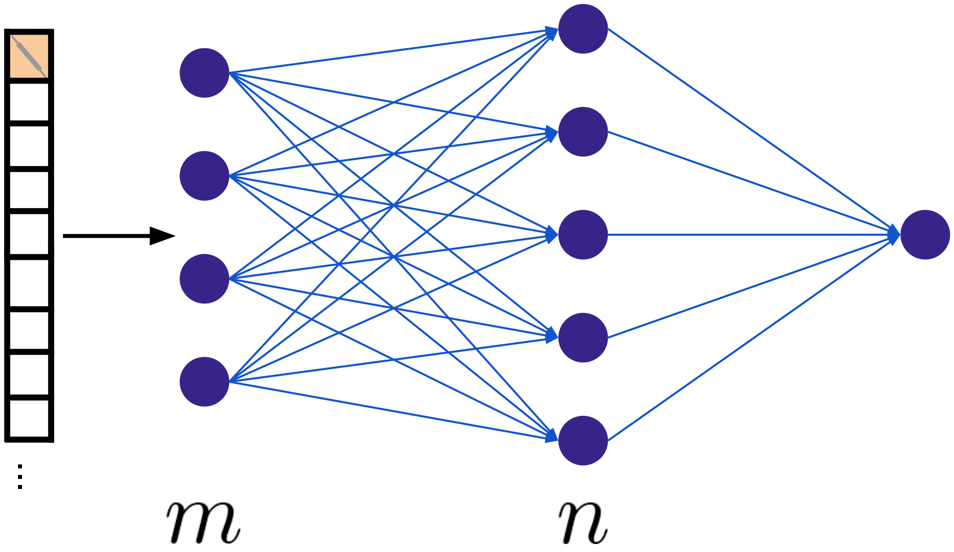
CNN: Fully-connected Layer



$$\begin{bmatrix} \theta^1_{11} & \theta^1_{12} & \theta^1_{13} & \dots & \theta^1_{1m} \\ \theta^1_{21} & \theta^1_{22} & \theta^1_{23} & \dots & \theta^1_{2m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \theta^1_{n1} & \theta^1_{n2} & \theta^1_{n3} & \dots & \theta^1_{nm} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{bmatrix} = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix}$$

$$\begin{bmatrix} \theta^2_{11} & \theta^2_{12} & \theta^2_{13} & \dots & \theta^2_{1n} \end{bmatrix} \sigma\left(\begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix} \right)$$

$$= \begin{bmatrix} h_1 \end{bmatrix}$$

Ignoring bias values for simplification

In this example, we're doing regression

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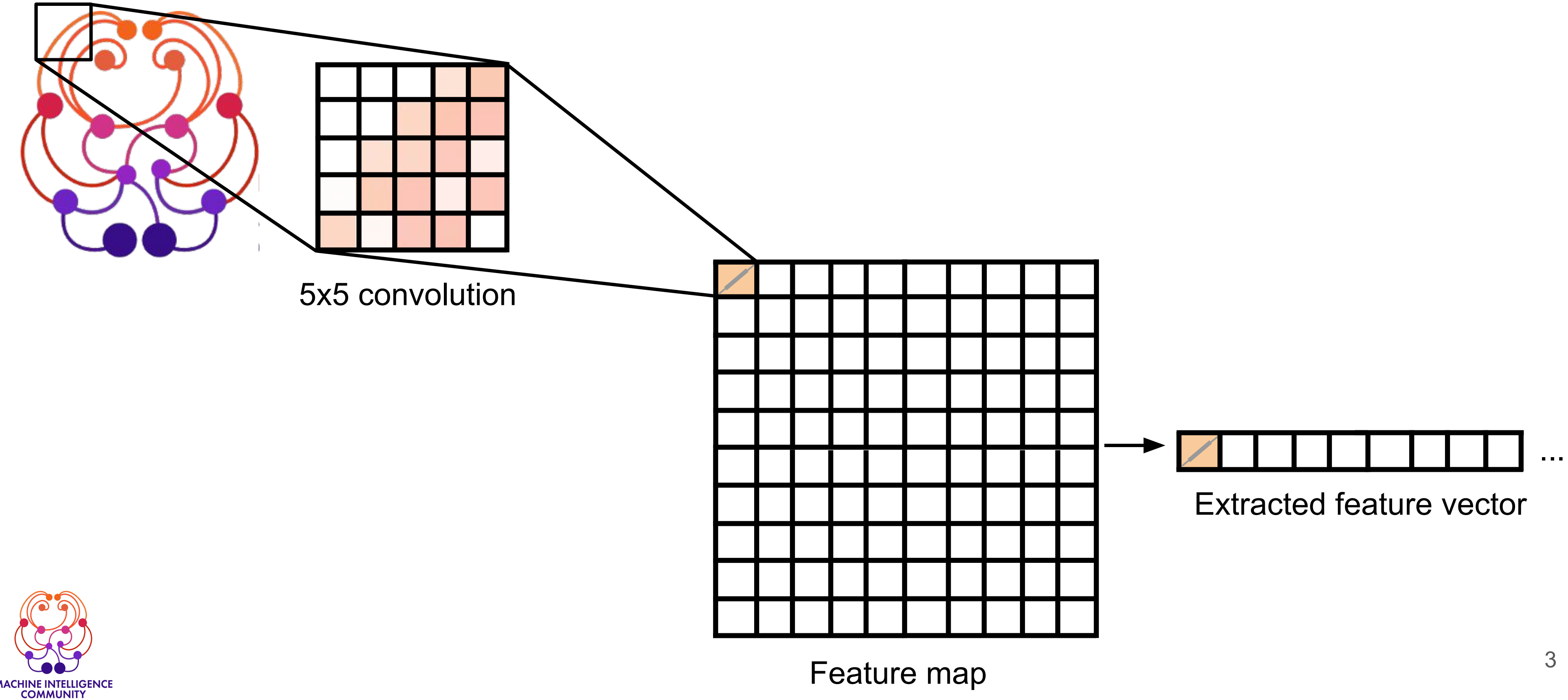
CNN: Automatic Feature Extraction



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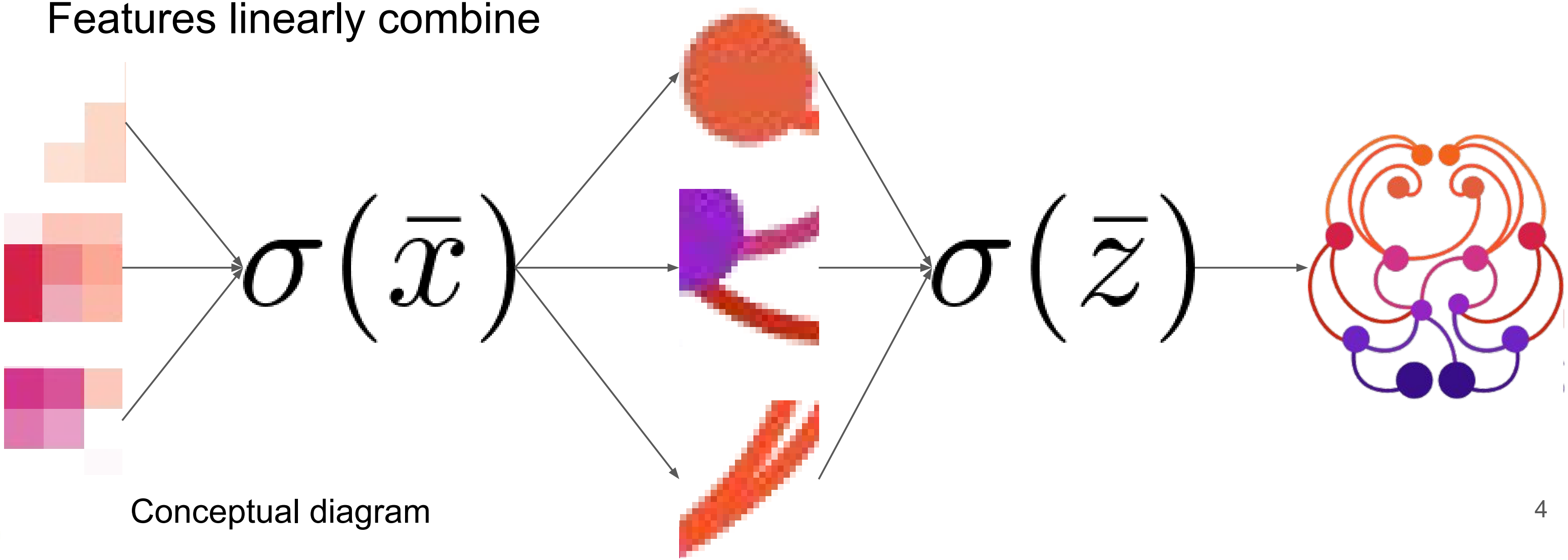
Feature Hierarchy

- Learned features become progressively more complex throughout the network
- Earlier layers contain more primitive features
- Features linearly combine



Conceptual diagram

Primitive features

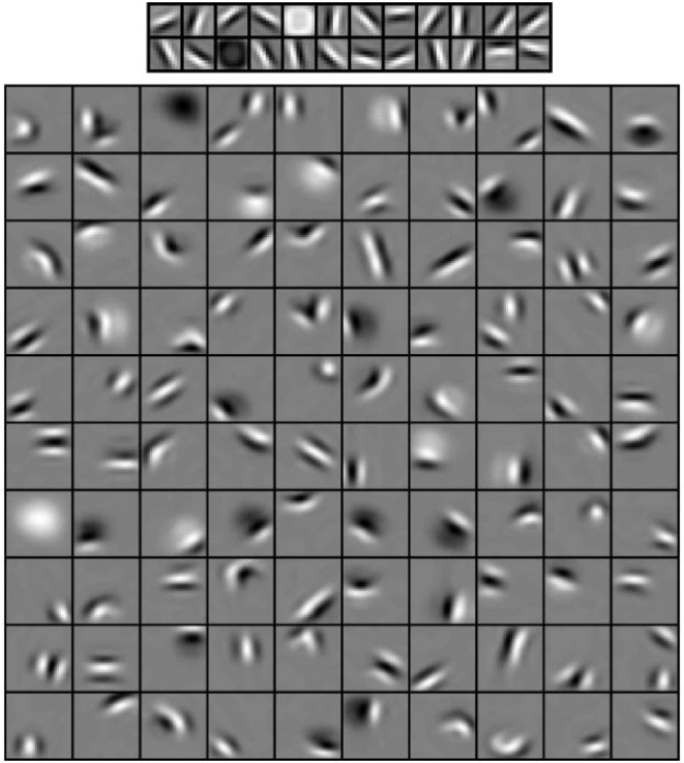


Image from Lee et al. 2011

Complex features

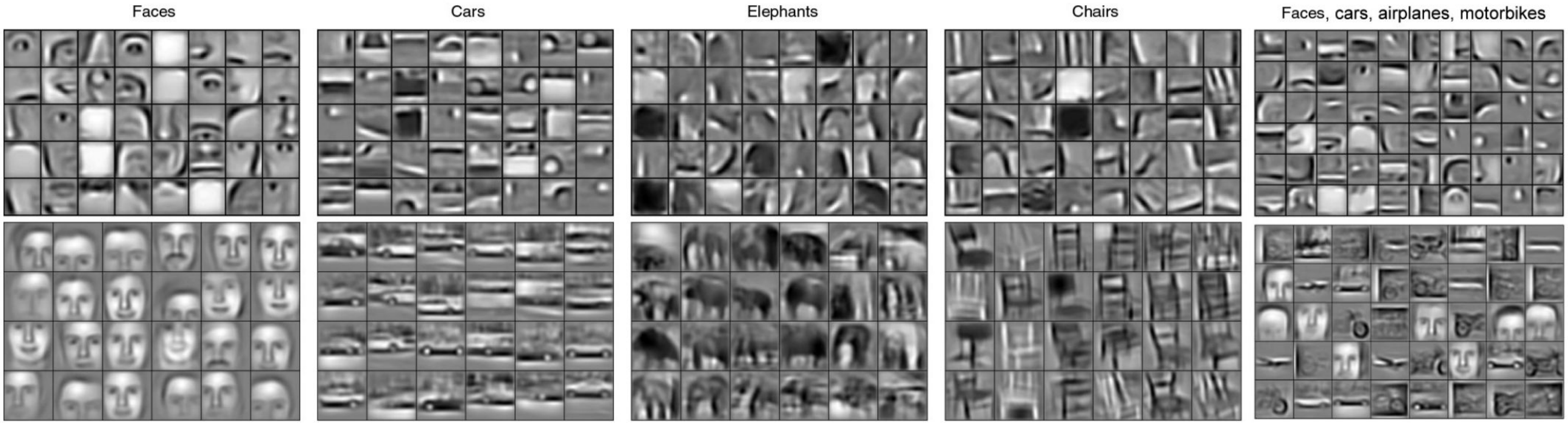
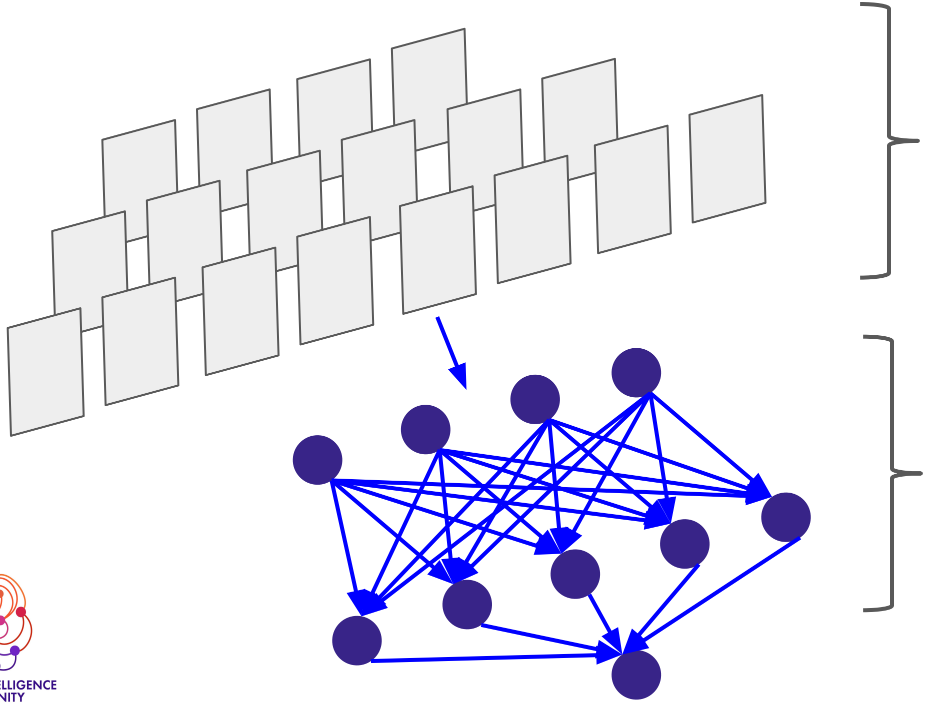


Image from Lee et al. 2011

How to reuse learned models?

- Would be useful to be able to reuse learned parameters and learned features



- Trained feature extractor contains features common among domain
- Reuse this part

- Trained fully-connected network contains features specific to dataset
- Can potentially reuse weights in latter layers as well

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Deep learning so far ...

- Convolutional neural networks allows us to capture compositional data and convert it into a hierarchical representation.
  - This approach have prove quite effective in classification task, especially in computer vision.
- While CNN is effective in computer vision task, it is also requires a lot of resources.
- CNN, Neural Networks, Backpropagation are not new. All of these techniques have been around since the 1980s. But why it’s popular now?

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ImageNet

- Both a collection of 14+ millions images that are categorised **by human** into roughly 20 thousands categories. This dataset also fuels the ImageNet challenge.

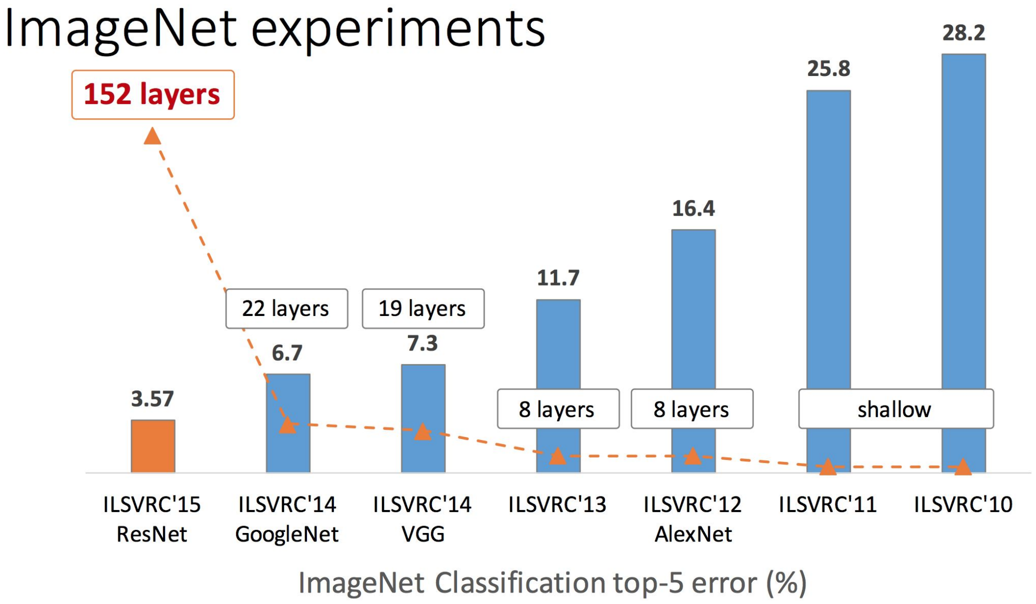

Image from He et al. 2016

The domain of data

- Finding large amount of data for every task we want our machine learning model to perform is hard.
    - e.g. doing machine translation on rare language pair.
    - e.g. data about cyber vulnerabilities exploits

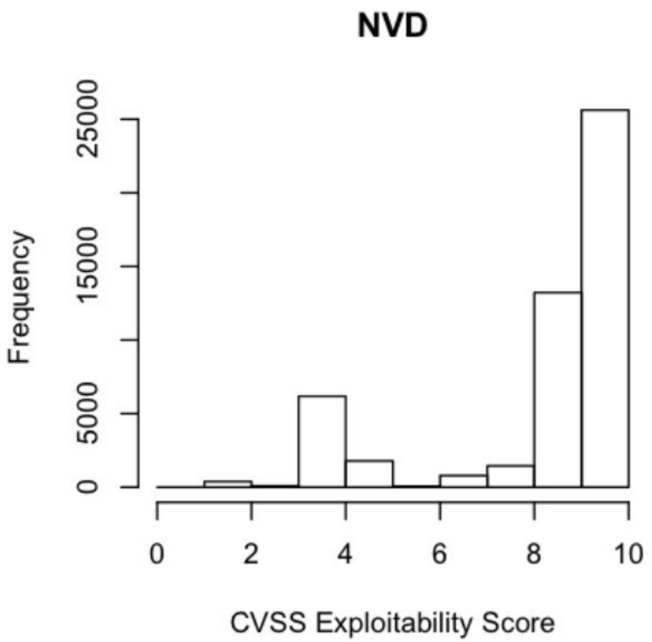

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Image from Allodi and Massacci 2013

The domain of data

- Sometime our input data varies.
  - e.g. speech recognition is challenging because every person's speech is a little bit different. Furthermore, there are different accent of the same language, thus one model for one language would not work well.

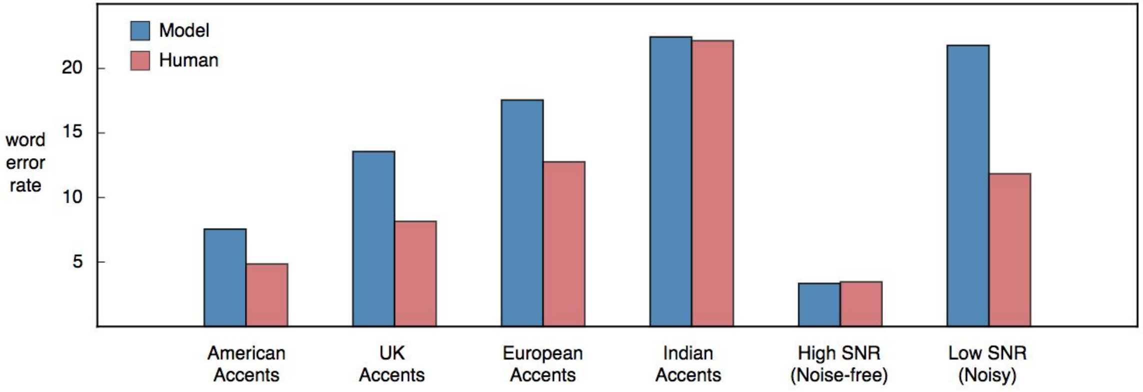

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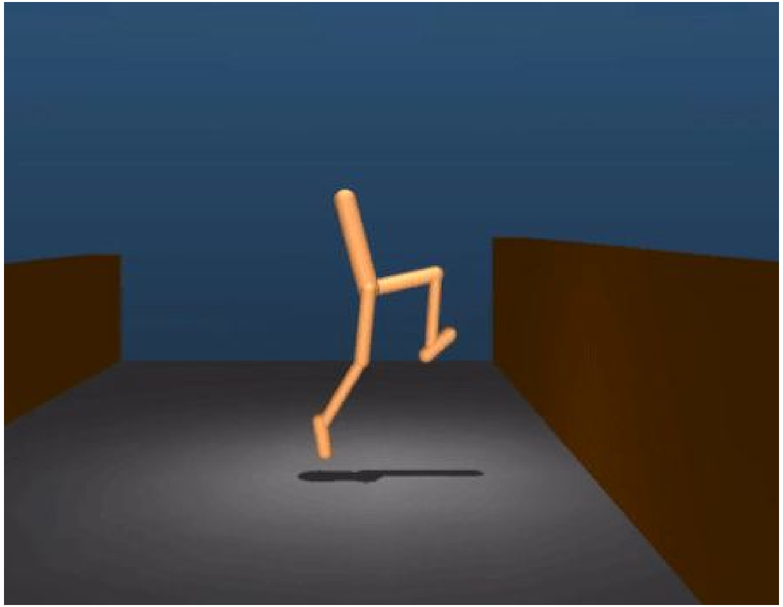
Chart from [Awni Hannun]

Learning from simulation

- Use a simulation of the real world to train a model.
  - Faster training time
  - Less costly
  - Able to repeat multiple time
- But the data from the simulation is still not the same data from the real world.
  - We need the ability to adapt the model from using the data in the simulated world to the data



DeepMind's simulated environment

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Image from DeepMind

So, transfer learning

- Utilise the feature extraction property of Convolutional Neural Networks
  - Reduce training time and computational cost.
  - Reduce the amount of data used.
- Improve performance with task where the data domain varies.
  - In general, instead of mapping data to output, we distill some “knowledge” about the data and use that to make a better machine learning model.

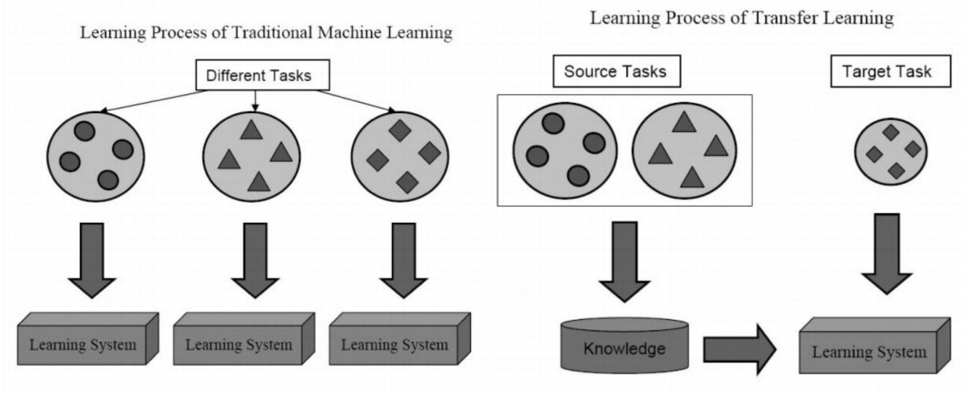

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Image from Pan and Yang 2010

More formally

$$\mathcal{D} = \{\mathcal{X}, P(X)\}$$

Domain

Feature space

Marginal probability distribution

When $D_s \neq D_t$ or $T_s \neq T_t$, **transfer learning** aims to improve the target predictive function (the conditional probability distribution) in D_t using knowledge from D_s and T_s

Task

Output/Label space

$$\mathcal{T} = \{\mathcal{Y}, P(Y|X)\}$$

Conditional probability distribution
(this is what's usually learnt)

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Different scenarios of transfer learning

The domains are different

$$\mathcal{X}_S \neq \mathcal{X}_T$$

The feature spaces of the data are different from each other.
E.g. different languages.

$$P(X_S) \neq P(X_T)$$

The marginal probability distributions of the data are different.
E.g. different topic of document.

The tasks are different

$$\mathcal{Y}_S \neq \mathcal{Y}_T$$

The label spaces are different.
E.g. classify the same document into different label depend on different task.

$$P(Y_S|X_S) \neq P(Y_T|X_T)$$

The learned functions are different.
E.g. the source and target distribution of the data is unbalanced compared to their class.

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Different setting of transfer learning

- Both domain and task are different -> **Unsupervised Transfer Learning**.
- Domains are different -> **Transductive Transfer Learning**
- Tasks are different -> **Inductive Transfer Learning**

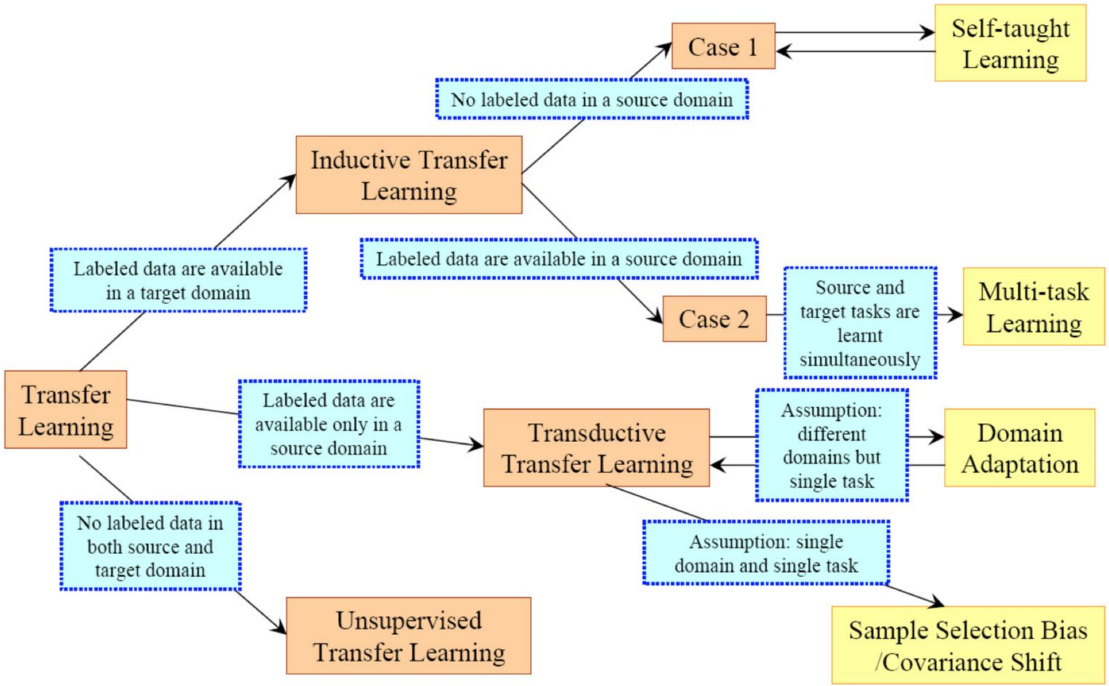
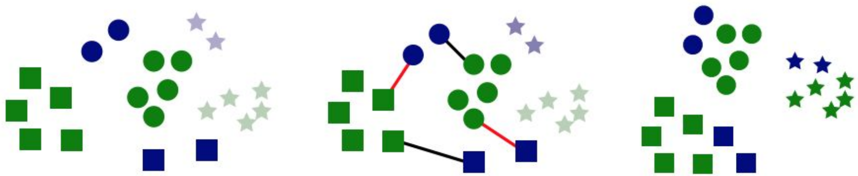


Image from [Pan and Yang 2010]

Domain Adaptation

- We are learning the same task but on different domain of data.
- To make our model adapt to the change in domain, we could make the two domain “closer” to each other.
    - Transform data from the domains into an invariant space (K. Saenko et al. 2010)



(a) Domain shift problem (b) Pairwise constraints (c) Invariant space

    - Make it an objective of the model to “confuse” the domains of the data (Ganin 2015)

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Image from Saenko et al. 2010

Domain confusion using backpropagation

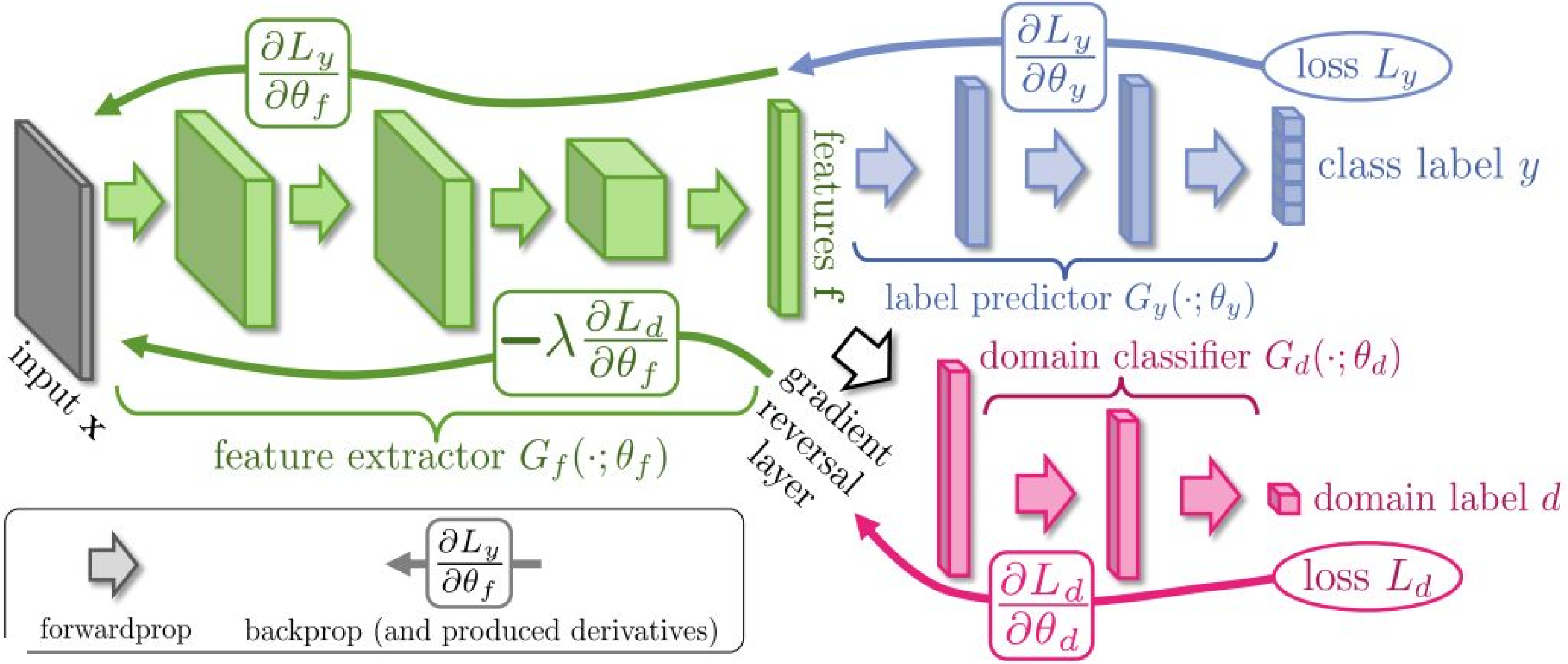

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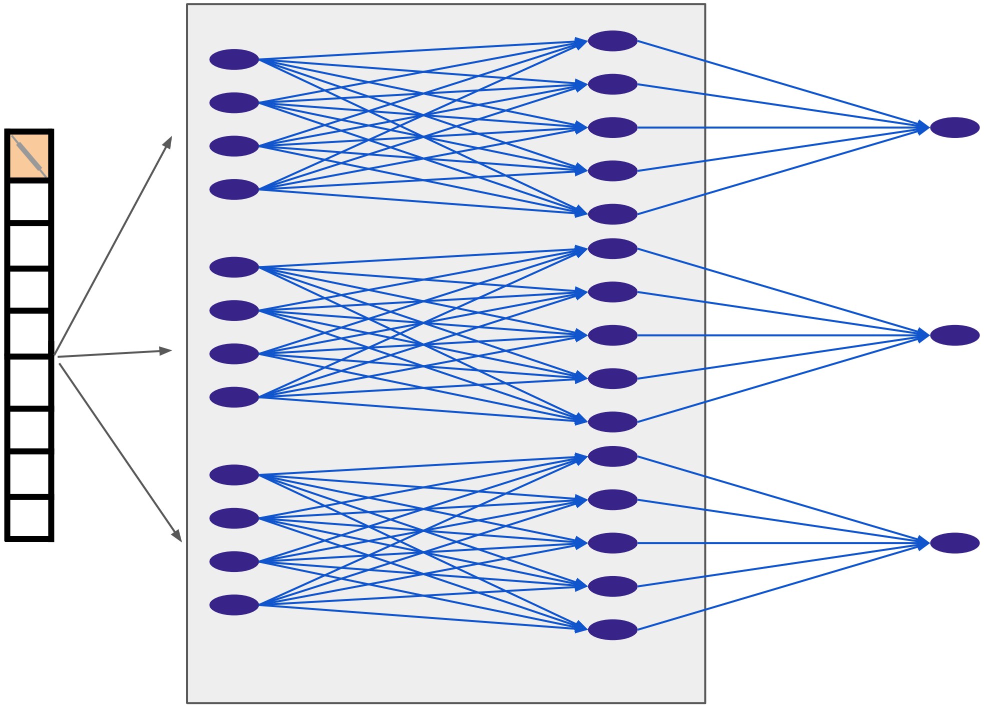
Image from Ganin and Lempitsky 2015

Multi-task learning



- Instead of training a model for each task, let's train one model for all the task and share the parameters for the models.
- This take advantage of the hierarchical representation of the data through the network.

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Few-shot, One-shot, Zero-shot learning

- Data is expensive. Can we use transfer learning to learn with less data?

- **One-shot** learning means that the model have one example of the class before it has to make the prediction and **zero-shot** learning is making prediction on brand new data.

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Example of few shot learning in human

- If you are not familiar with this spiky fruit on the left here, it’s a durian.
- Human has the ability to learn/understand concepts, ideas, or objects from very small “training” example.

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Image from Wikimedia Commons

Example of few shot learning in human

- So if you see the image of this spiky fruit again, you would easily be able to recognise that's it's a durian.
    - In essence, you only require one or few training example to "learn" new thing.

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Image from Wikimedia Commons

Example of zero shot learning in human

- Furthermore, human can generalise from other knowledge.
  - The wug test developed by Berko Gleason (1958) show that very young child can apply morphological rule to unknown words.
  - Here, we don’t know the plural form of the word “wug”, but we are able to formulate it anyway.

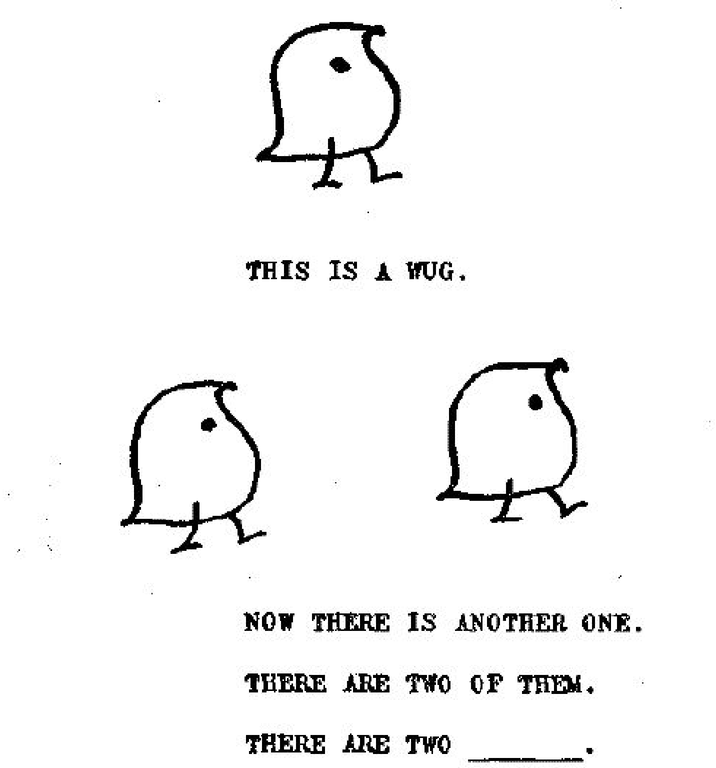

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Image from Berko 1958

Word-embedding

- Turns words to vector representation.
- Models like *word2vec* exploit the fact that semantically similar words tend to be around similar words.
- Vector representation have semantics value.

Image from Olah 2014

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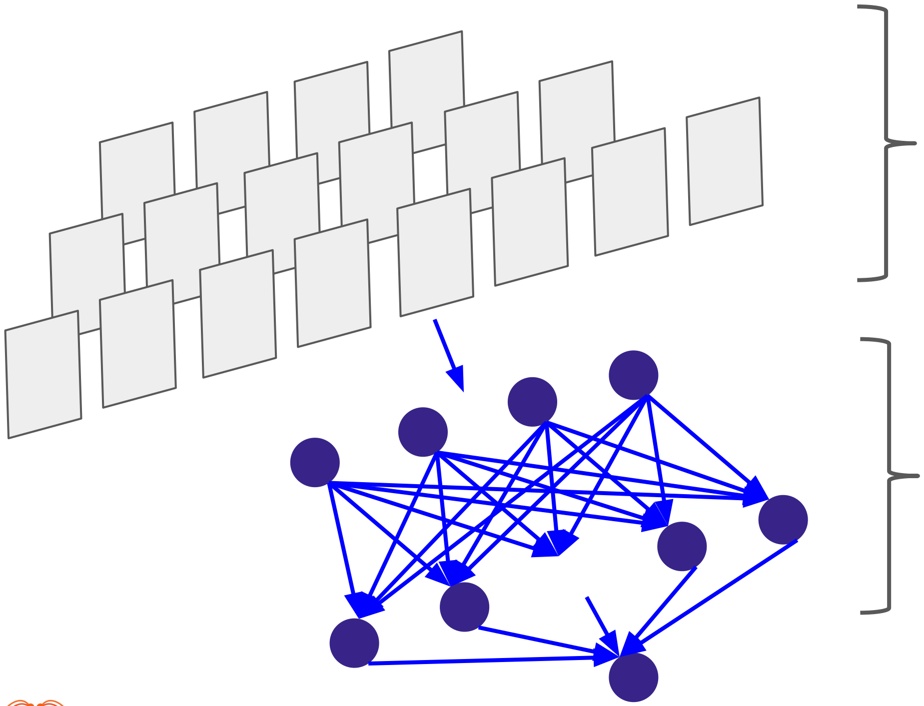
Pre-training and fine-tuning



- **Fine-tuning** is when you have a different but related dataset and you want to train the whole model to better fit what you have.
- **Pre-train** models have all the weights already trained. Just make a new Fully Connected layer at the end and retrain the layer.

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Pretrained models with PYTORCH

```python
import torchvision.models as models
resnet18 = models.resnet18(pretrained=True)
alexnet = models.alexnet(pretrained=True)
squeezenet = models.squeezenet1_0(pretrained=True)
vgg16 = models.vgg16(pretrained=True)
densenet = models.densenet161(pretrained=True)
inception = models.inception_v3(pretrained=True)
```

```python
for param in model_conv.parameters():
    param.requires_grad = False
```

```python
num_ftrs = model_conv.fc.in_features
model_conv.fc = nn.Linear(num_ftrs, 3)
```

- Import and instantiate pretrained model
- Remove the output layer of model
- Append a randomly initialized classifier and fine-tune

Try it out!

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References & Further Reading

1. http://machinelearning.wustl.edu/mlpapers/paper_files/ICML2011Glorot_342.pdf
2. http://www.deeplearningbook.org/contents/representation.html
3. http://anthropology.uwo.ca/faculty/creider/027/wugs.pdf
4. https://www.cs.princeton.edu/~rajeshr/papers/cacm2011-researchHighlights-convDBN.pdf
5. http://ruder.io/transfer-learning
6. http://ieeexplore.ieee.org/document/5288526/

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Upcoming Events

MIC Paper signup: https://goo.gl/iAm6TL
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BUMIC paper discussion:

Paper: **Decoupled Neural Interfaces using Synthetic Gradients**
Location: Fishbowl Conference Room
Date: 11.06.17 Time: 7 PM

Next workshop:

Topic: Sequential Data
Location: BU Hariri Seminar Room
Date: 11.07.17 Time: 7 PM

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