Transfer Learning

Transfer Learning - Overview

		Source Data (not directly related to the task)	
		labelled	unlabeled
Target Data	labelled	Model Fine-tuning	
	unlabeled		

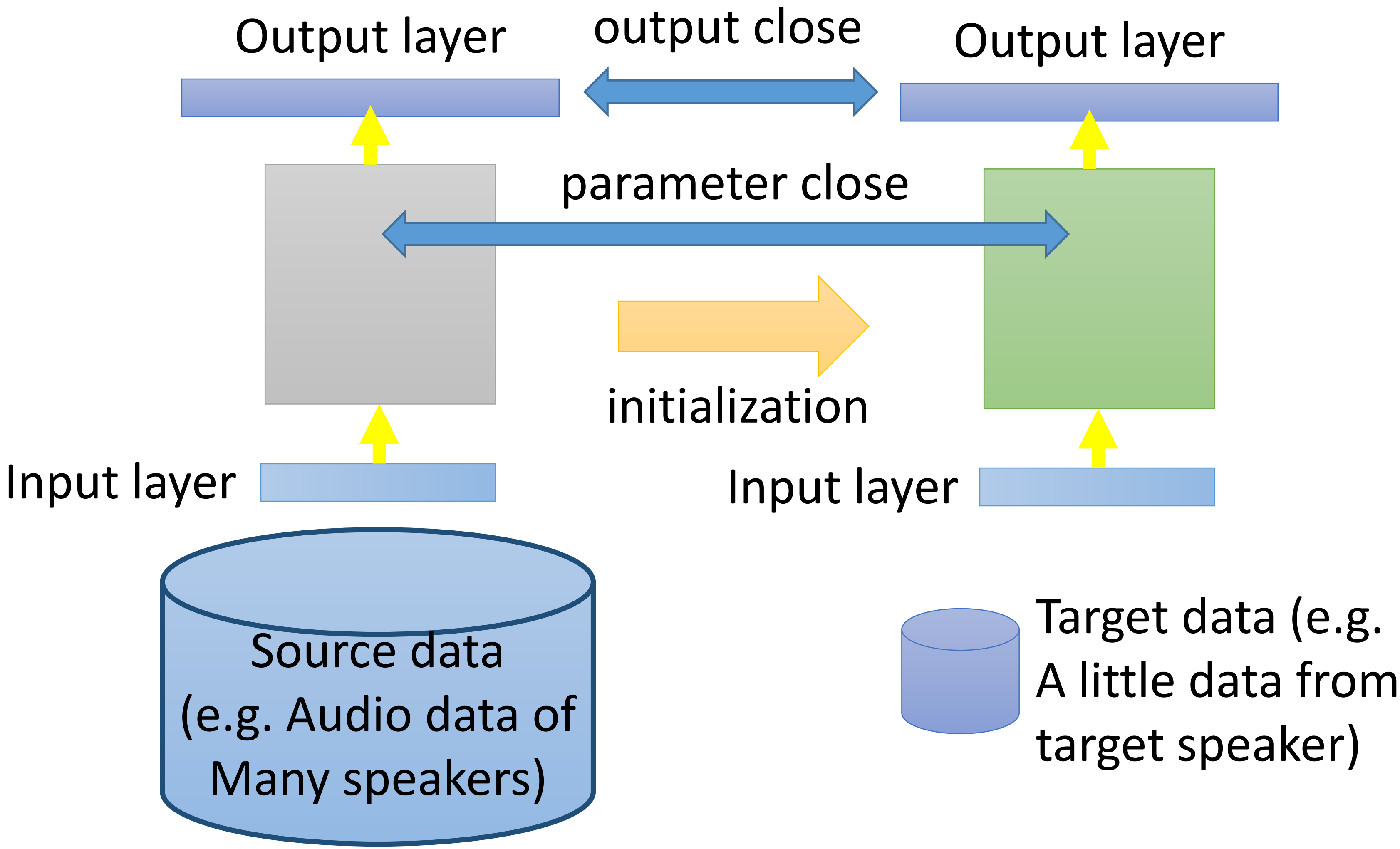
Warning: different terminology in different literature

Model Fine-tuning

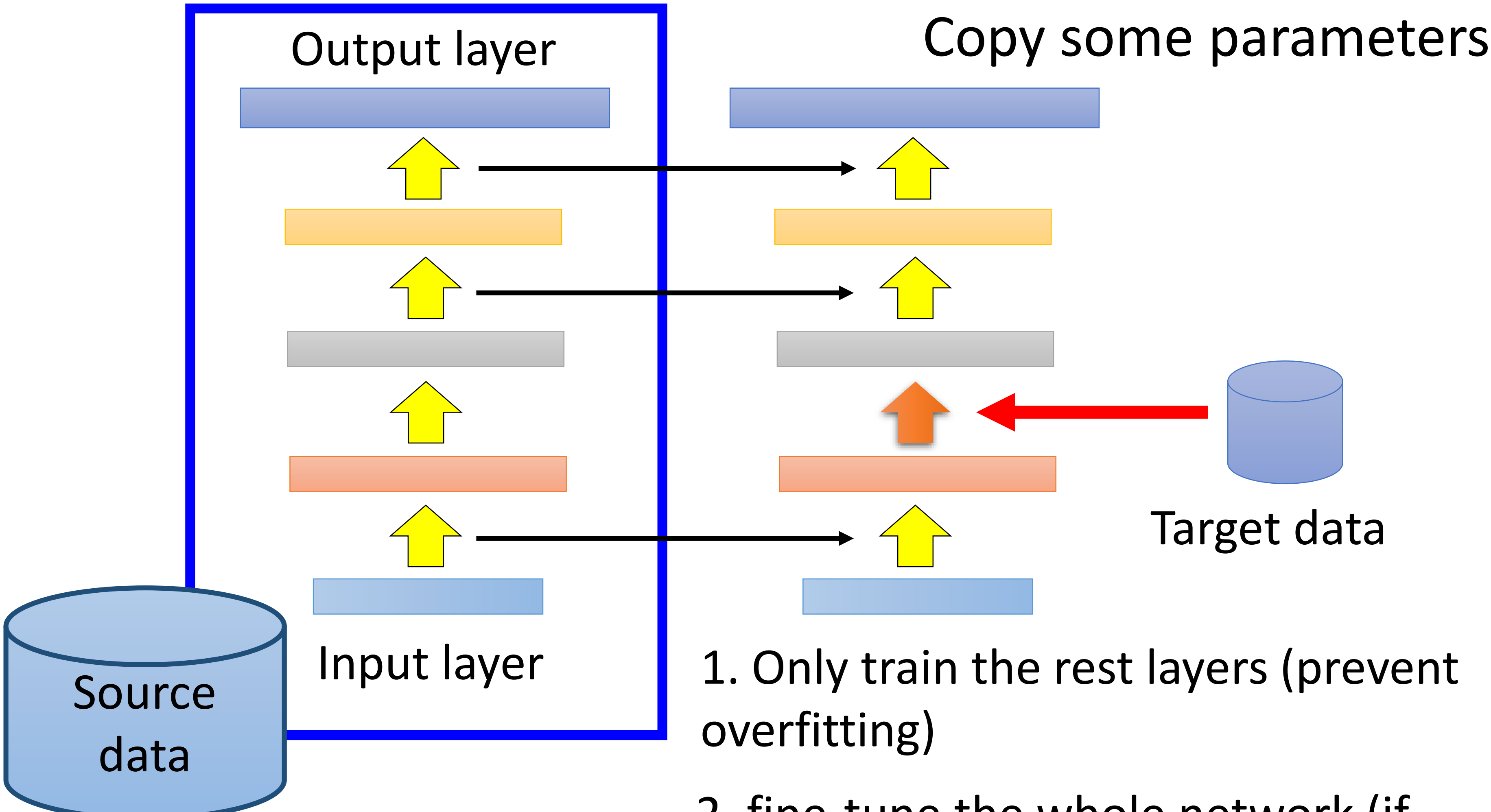
One-shot learning: only a few examples in target domain

- Task description
  - Source data: (x^s, y^s) ⇦ A large amount
  - Target data: (x^t, y^t) ⇦ Very little
- Example: (supervised) speaker adaption
  - Source data: audio data and transcriptions from many speakers
  - Target data: audio data and its transcriptions of specific user
- Idea: training a model by source data, then fine-tune the model by target data
  - Challenge: only limited target data, so be careful about overfitting

Conservative Training



Layer Transfer

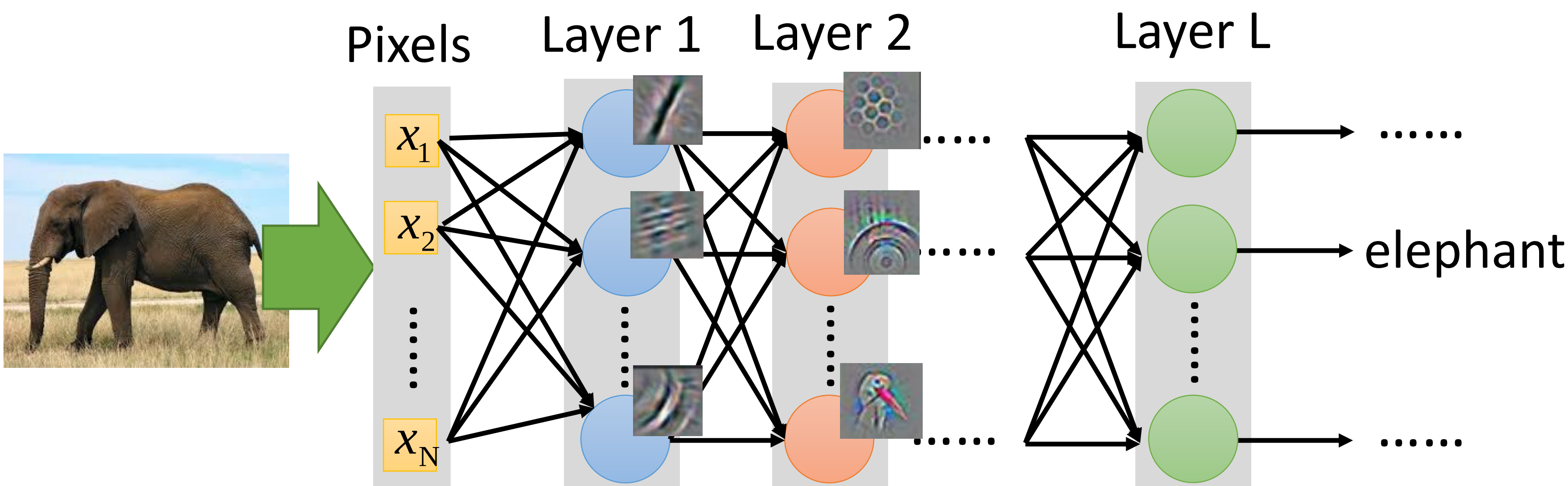


1. Only train the rest layers (prevent overfitting)

2. fine-tune the whole network (if there is sufficient data)

Layer Transfer

- Which layer can be transferred (copied)?
  - Speech: usually copy the last few layers
  - Image: usually copy the first few layers



Transfer Learning - Overview

		Source Data (not directly related to the task)	
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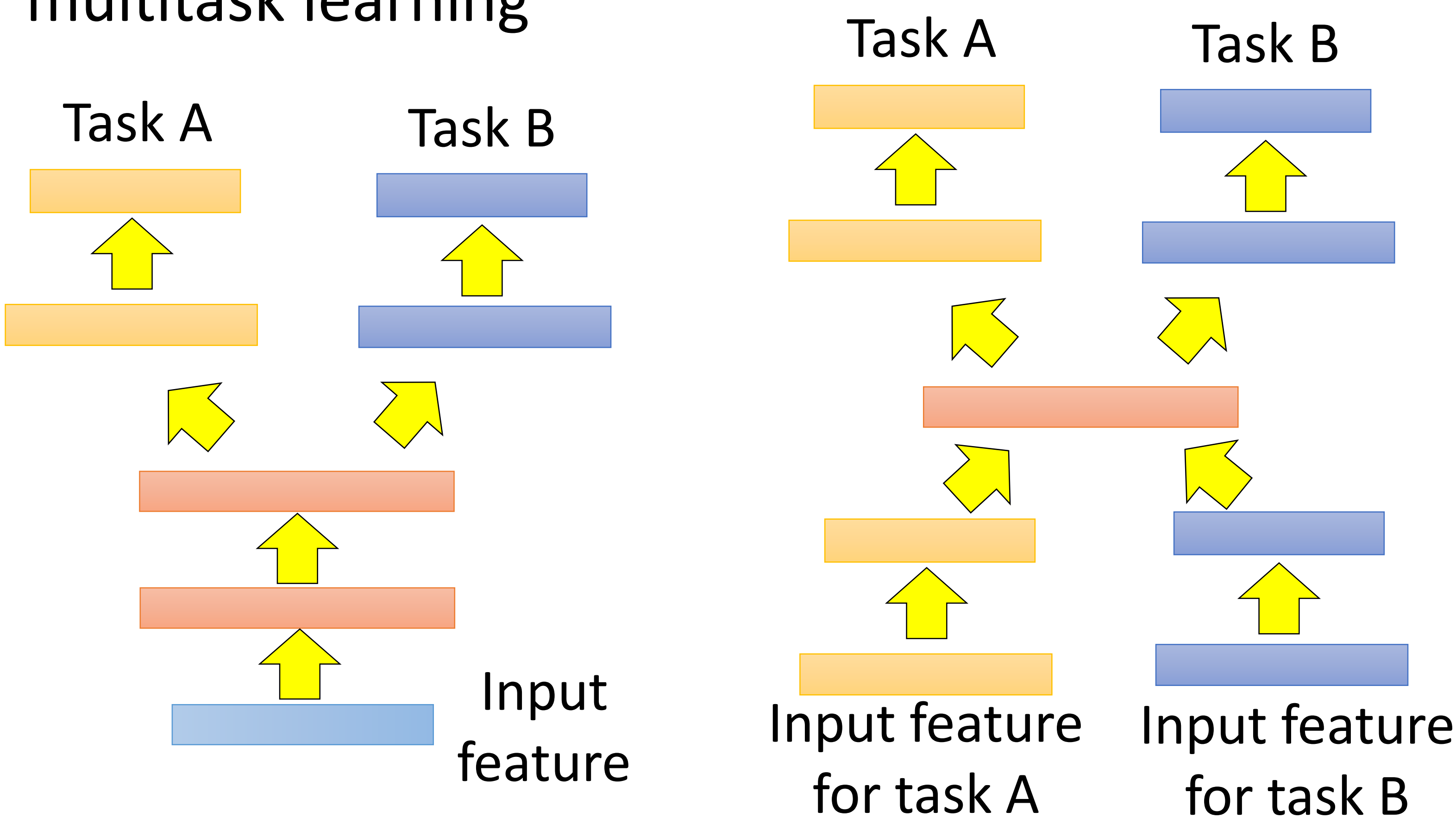
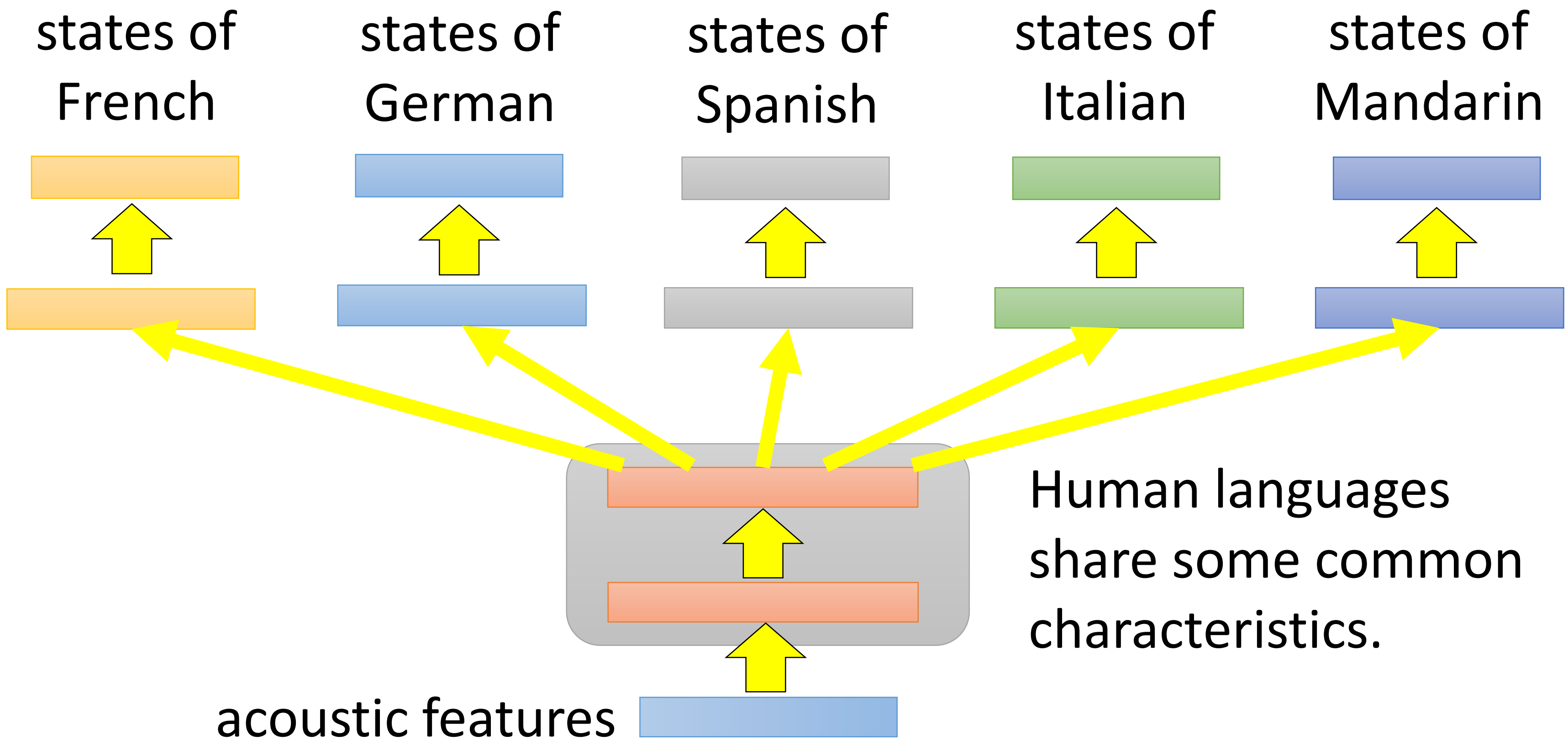
Target Data	labelled	Fine-tuning Multitask Learning	
	unlabeled		

Multitask Learning

- The multi-layer structure makes NN suitable for multitask learning



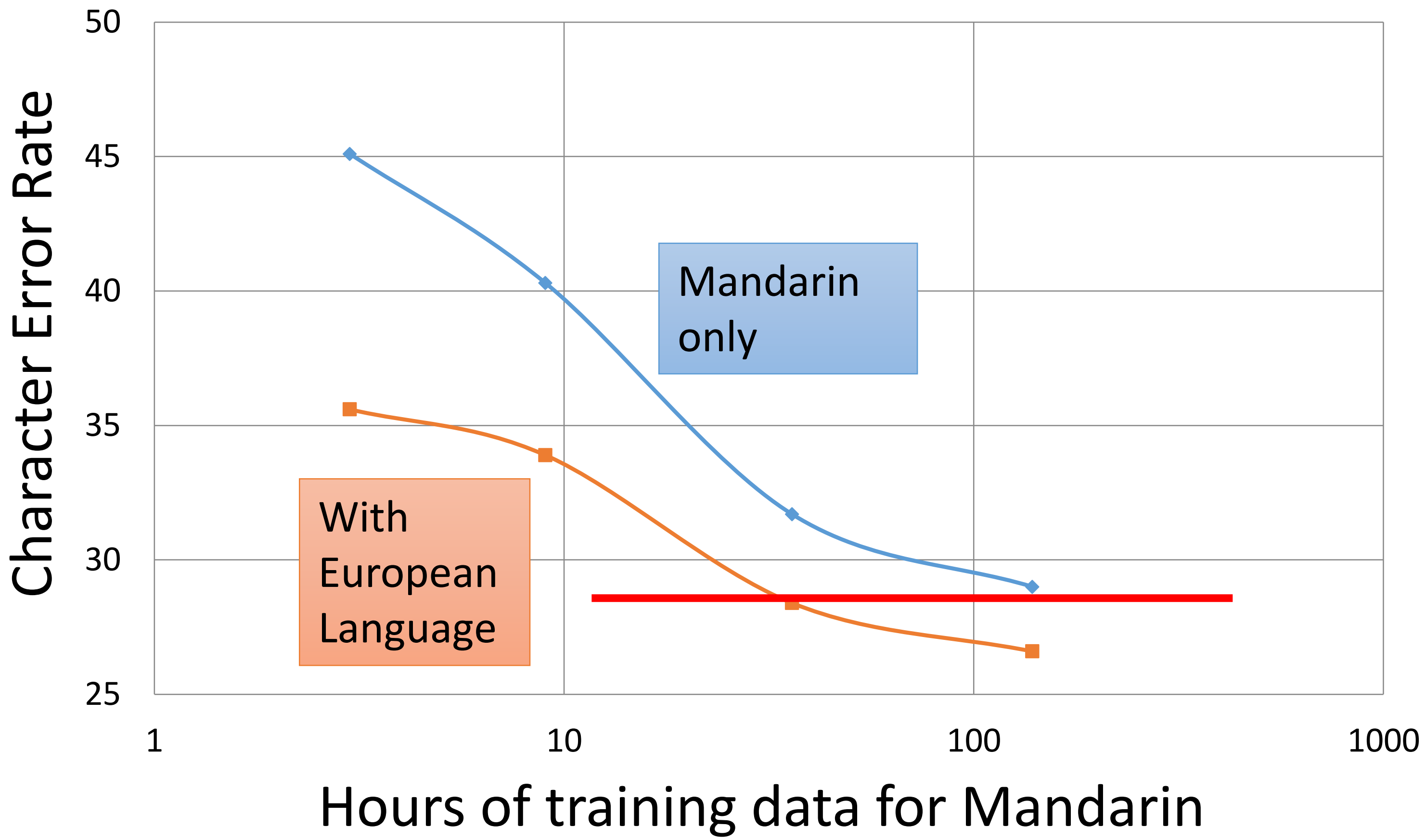
Multitask Learning - Multilingual Speech Recognition



Human languages share some common characteristics.

Similar idea in translation: Daxiang Dong, Hua Wu, Wei He, Dianhai Yu and Haifeng Wang, "Multi-task learning for multiple language translation.", ACL 2015

Multitask Learning - Multilingual



Huang, Jui-Ting, et al. "Cross-language knowledge transfer using multilingual deep neural network with shared hidden layers." *ICASSP, 2013*

Transfer Learning - Overview

		Source Data (not directly related to the task)	
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Target Data	labelled	Fine-tuning Multitask Learning	
	unlabeled	Domain-adversarial training	

Task description

- Source data: (x^s, y^s) → Training data
- Target data: (x^t) → Testing data

Same task, mismatch

MNIST

SOURCE

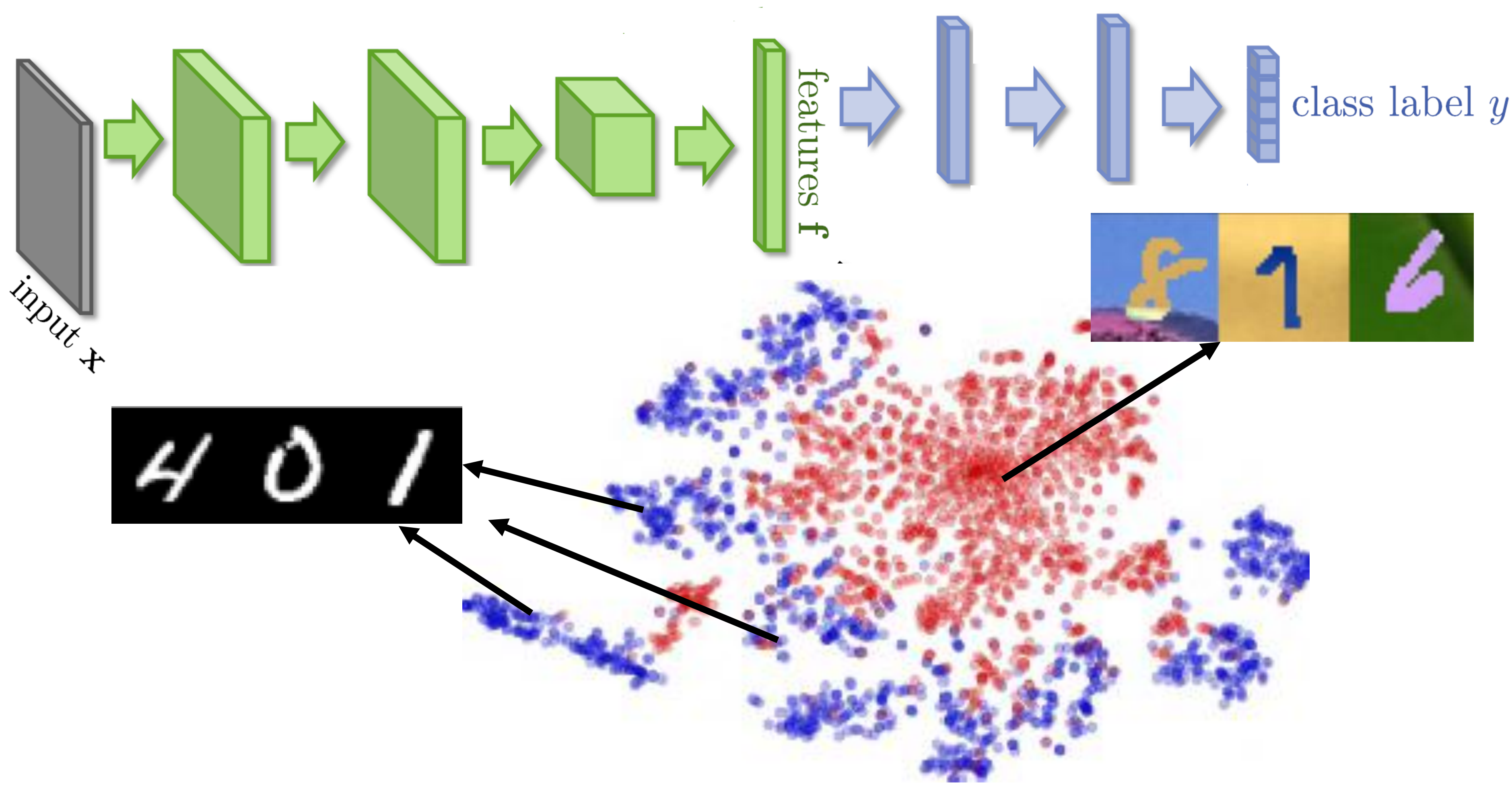
TARGET

with label

without label

MNIST-M

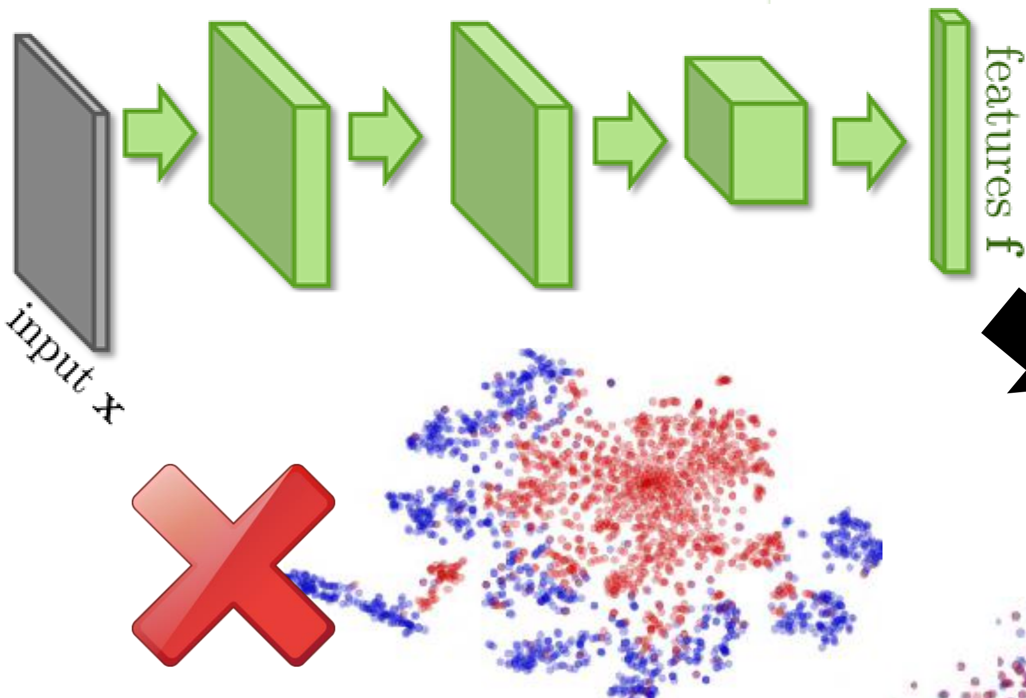
Domain-adversarial training



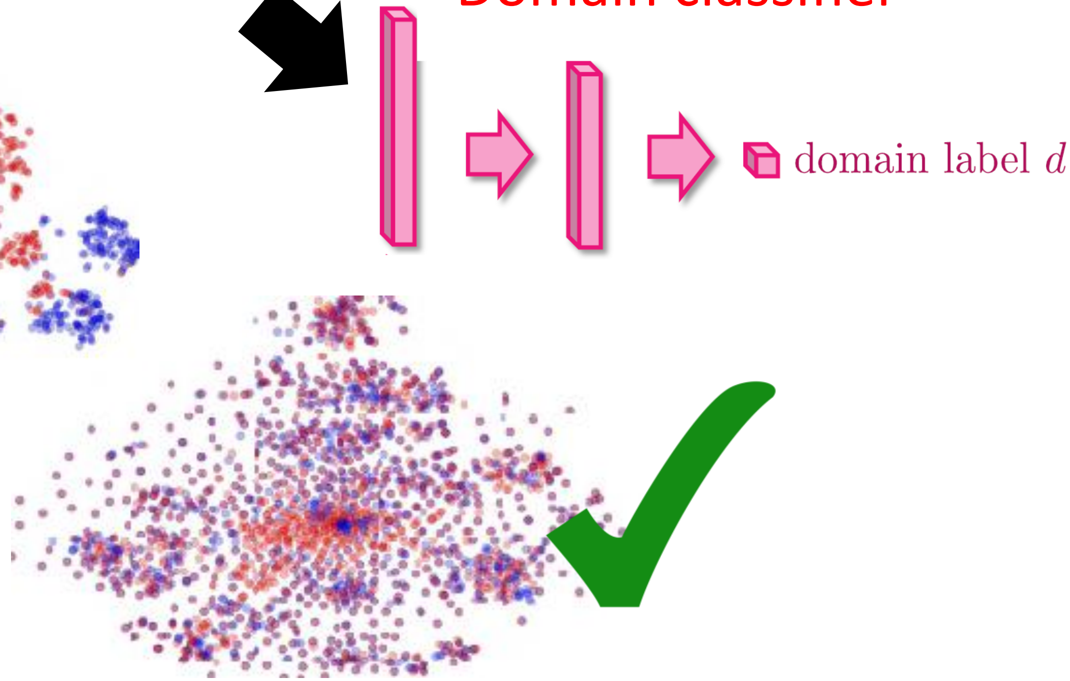
Domain-adversarial training

Similar to GAN

Too easy to feature extractor ……



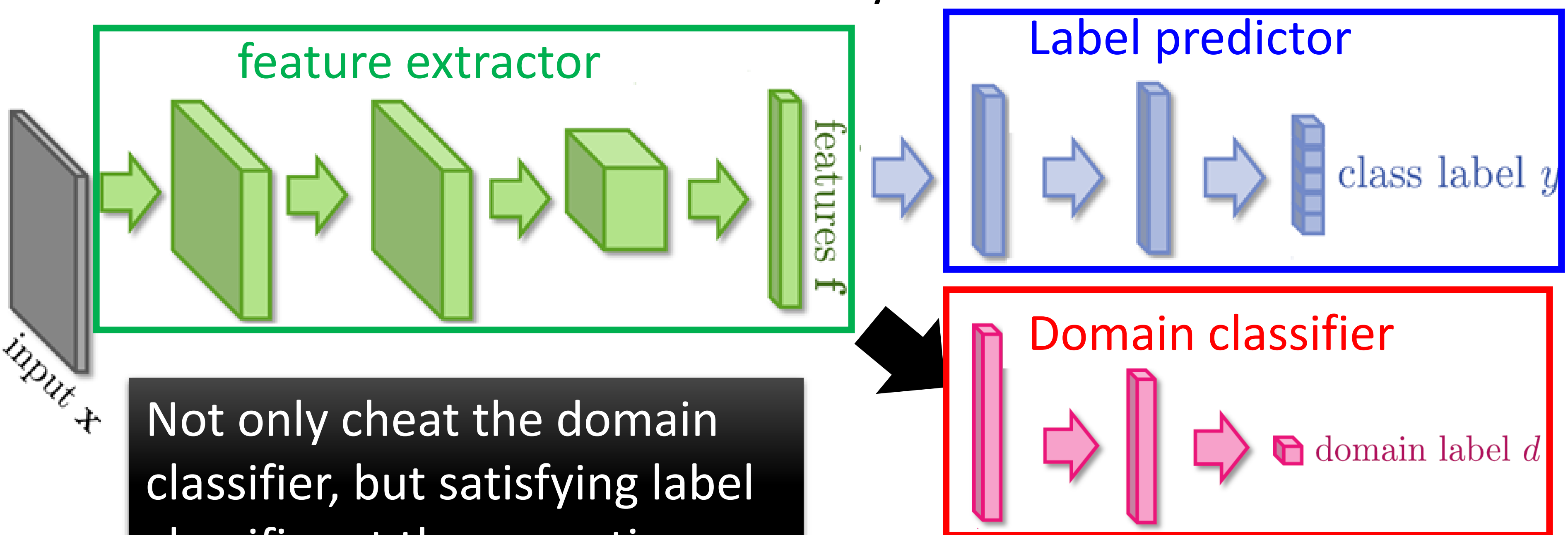
Domain classifier



Domain-adversarial training

Maximize label classification accuracy + minimize domain classification accuracy

Maximize label classification accuracy

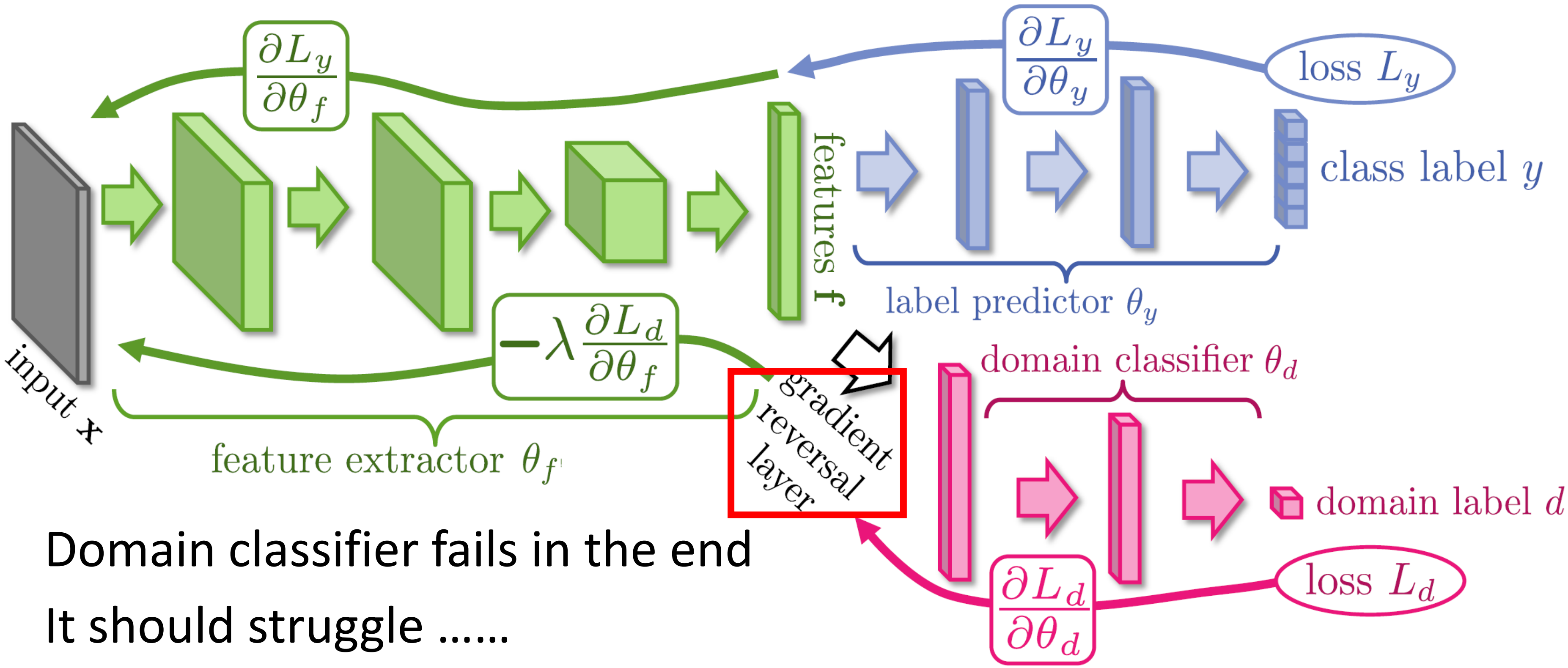


Not only cheat the domain classifier, but satisfying label classifier at the same time

Maximize domain classification accuracy

This is a big network, but different parts have different goals.

Domain-adversarial training



Domain classifier fails in the end

It should struggle ……

Yaroslav Ganin, Victor Lempitsky, Unsupervised Domain Adaptation by Backpropagation, ICML, 2015

Hana Ajakan, Pascal Germain, Hugo Larochelle, François Laviolette, Mario Marchand, Domain-Adversarial Training of Neural Networks, JMLR, 2016

Domain-adversarial training

METHOD	SOURCE / TARGET	MNIST / MNIST-M	SYN NUMBERS / SVHN	SVHN / MNIST	SYN SIGNS / GTSRB
SOURCE ONLY		.5749	.8665	.5919	.7400
SA (FERNANDO ET AL., 2013)		.6078 (7.9%)	.8672 (1.3%)	.6157 (5.9%)	.7635 (9.1%)
PROPOSED APPROACH		**.8149** (57.9%)	**.9048** (66.1%)	**.7107** (29.3%)	**.8866** (56.7%)
TRAIN ON TARGET		.9891	.9244	.9951	.9987

Yaroslav Ganin, Victor Lempitsky, Unsupervised Domain Adaptation by Backpropagation, ICML, 2015

Hana Ajakan, Pascal Germain, Hugo Larochelle, François Laviolette, Mario Marchand, Domain-Adversarial Training of Neural Networks, JMLR, 2016

Transfer Learning - Overview

		Source Data (not directly related to the task)	
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Target Data	labelled	Fine-tuning Multitask Learning	
	unlabeled	Domain-adversarial training Zero-shot learning	

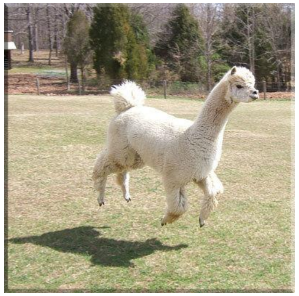
Zero-shot Learning

- Source data: (x^s, y^s) → Training data
- Target data: (x^t) → Testing data

Different tasks

x^s:   ……

y^s: cat dog ……

x^t :  

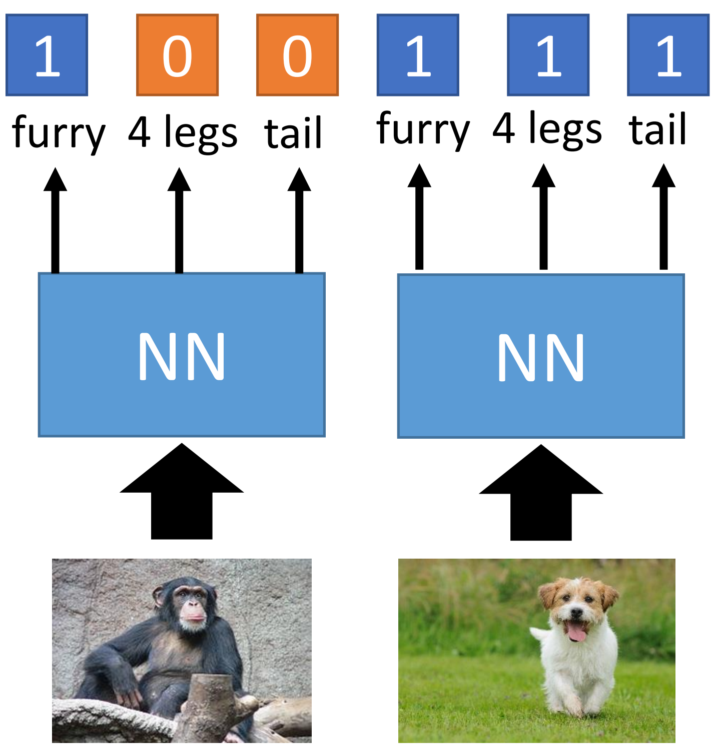
In speech recognition, we can not have all possible words in the source (training) data.

How we solve this problem in speech recognition?

Zero-shot Learning

- Representing each class by its attributes

<u>Training</u>



Database

attributes

class

	furry	4 legs	tail	…
Dog	O	O	O	
Fish	X	X	O	
Chimp	O	X	X	
…				

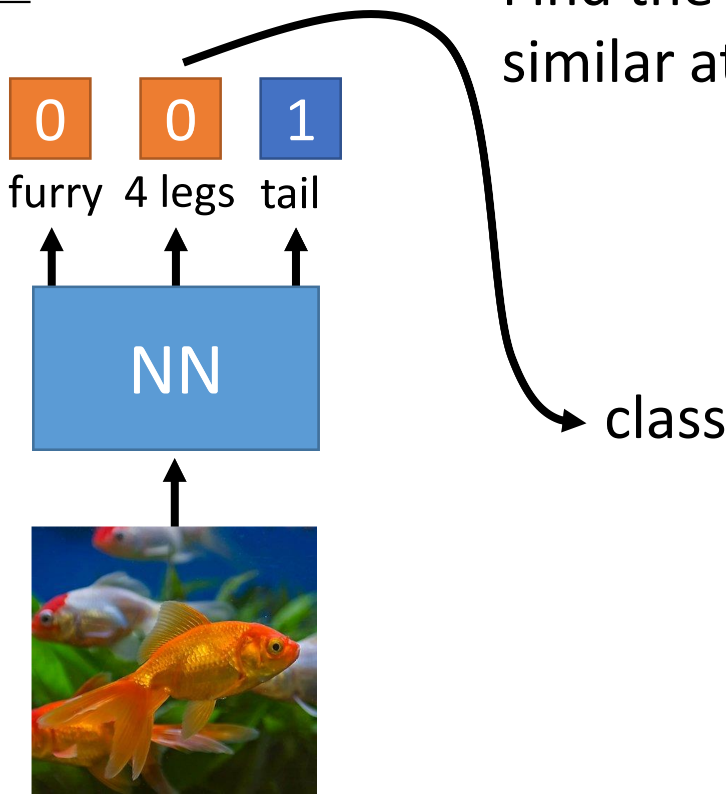
sufficient attributes for one to one mapping

Zero-shot Learning

- Representing each class by its attributes

Testing

Find the class with the most similar attributes



attributes

	furry	4 legs	tail	…
Dog	O	O	O	
Fish	X	X	O	
Chimp	O	X	X	
…				

sufficient attributes for one to one mapping

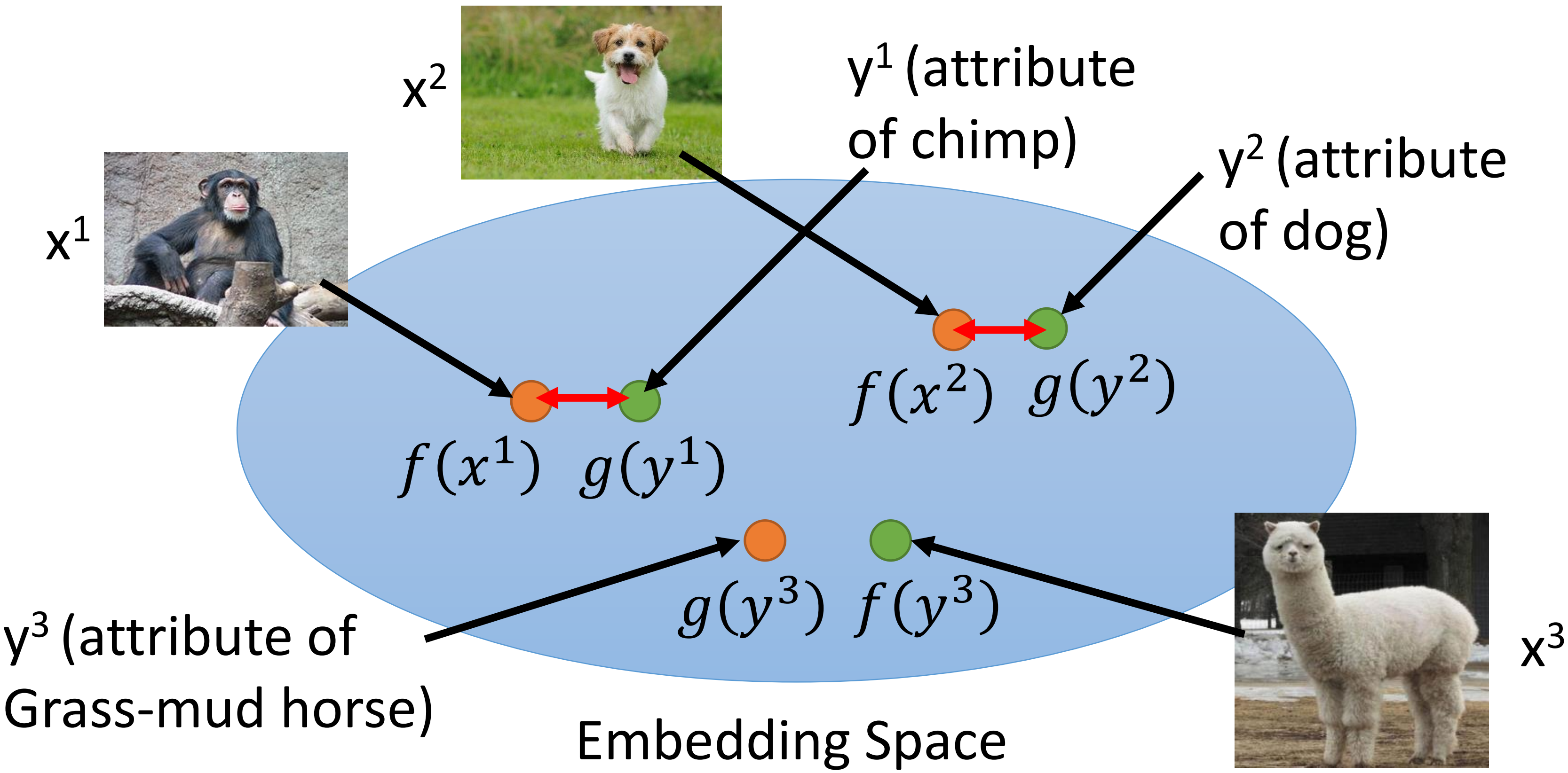
Zero-shot Learning

$f(*)$ and $g(*)$ can be NN.

Training target:

$f(x^n)$ and $g(y^n)$ as close as possible

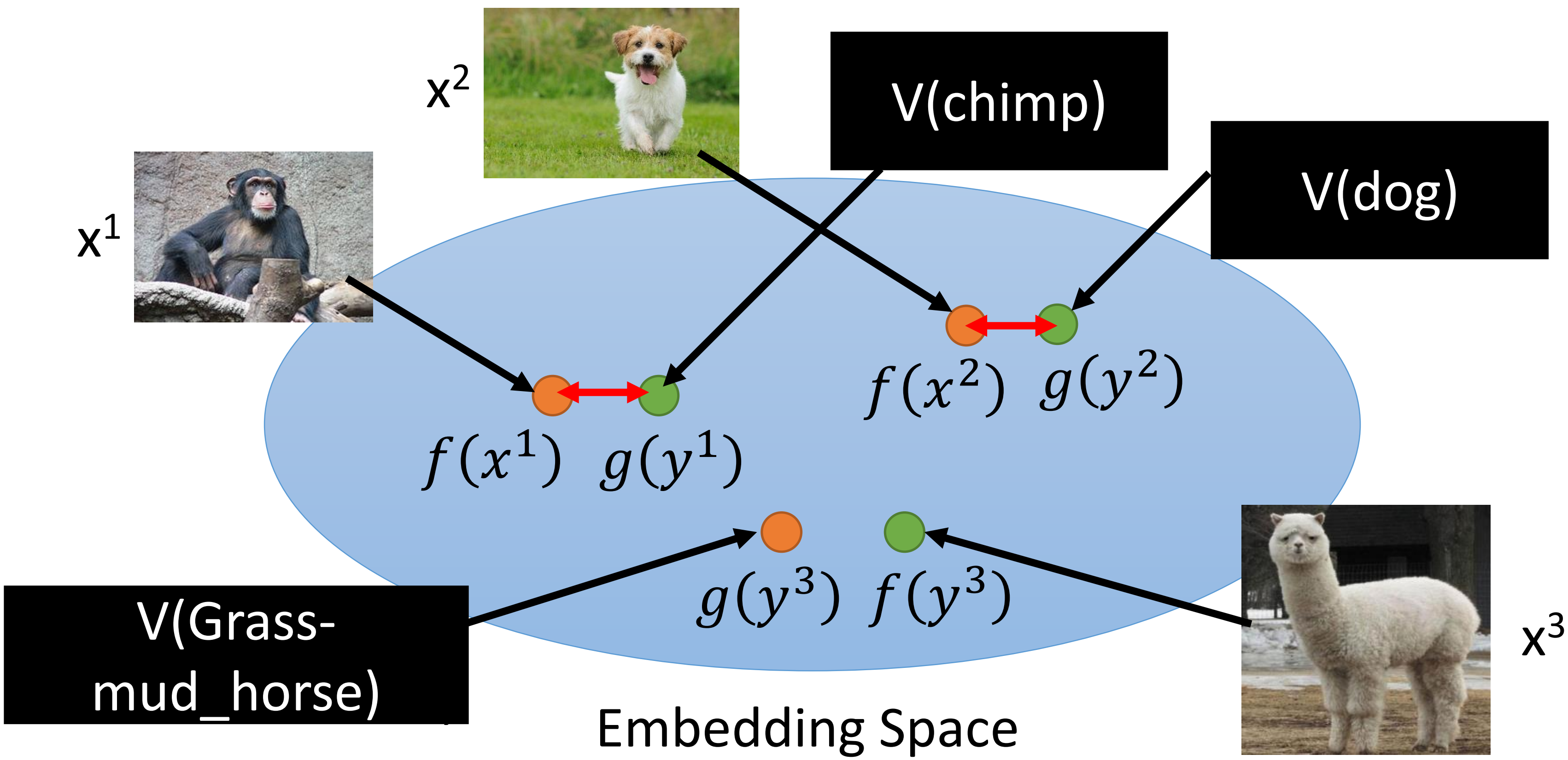
- Attribute embedding



Zero-shot Learning

What if we don't have database

- Attribute embedding + word embedding



Zero-shot Learning

$$f^*, g^* = arg \min_{f,g} \sum_n \| f(x^n) - g(y^n) \|_2$$

Problem?

$$f^*, g^* = arg \min_{f,g} \sum_n max\left(0, k - f(x^n) \cdot g(y^n) + \max_{m \neq n} f(x^n) \cdot g(y^m)\right)$$

Margin you defined

Zero loss: $k - f(x^n) \cdot g(y^n) + \max_{m \neq n} f(x^n) \cdot g(y^m) < 0$

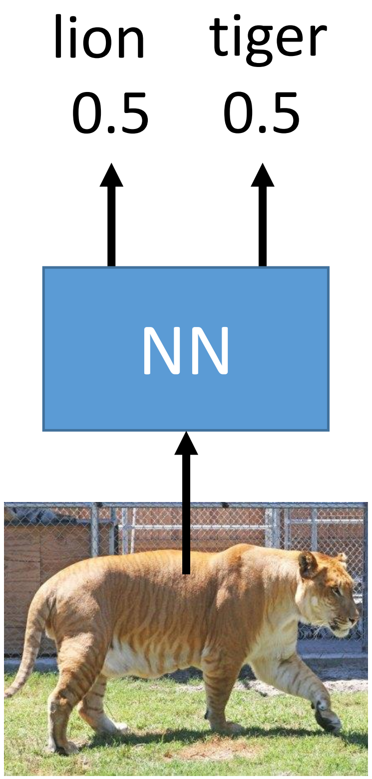
$$\underline{f(x^n) \cdot g(y^n)} - \underline{\max_{m \neq n} f(x^n) \cdot g(y^m)} > k$$

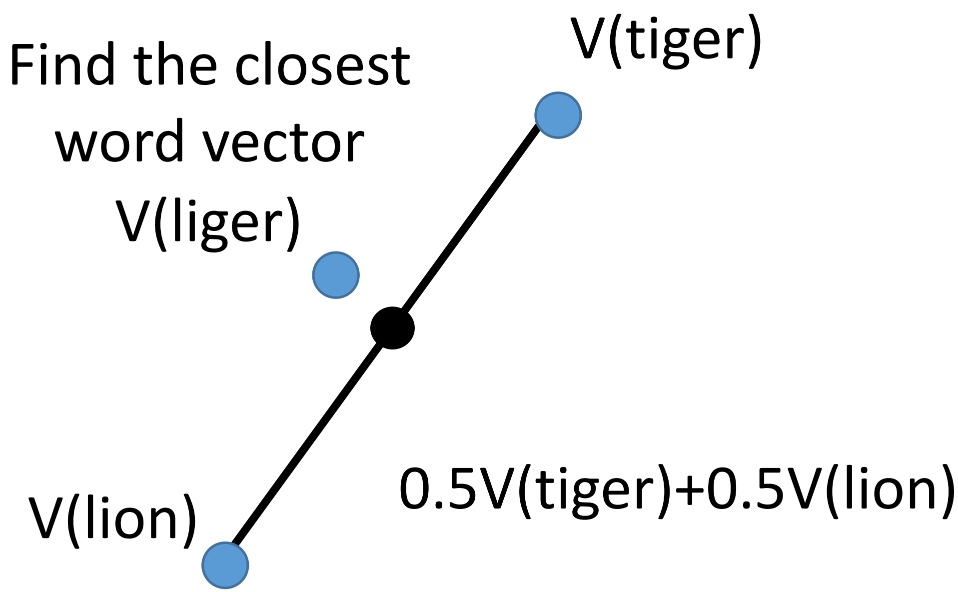
$f(x^n)$ and $g(y^n)$ as close

$f(x^n)$ and $g(y^m)$ not as close

Zero-shot Learning

- Convex Combination of Semantic Embedding





Only need off-the-shelf NN for ImageNet and word vector

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	unlabeled	Domain-adversarial training Zero-shot learning	Self-taught Clustering Wenyuan Dai, Qiang Yang, Gui-Rong Xue, Yong Yu, "Self-taught clustering", ICML 2008

Different from semi-supervised learning

Self-taught learning

- Learning to extract better representation from the source data (unsupervised approach)
- Extracting better representation for target data

Domain	Unlabeled data	Labeled data	Classes	Raw features
Image classification	10 images of outdoor scenes	Caltech101 image classification dataset	101	Intensities in 14x14 pixel patch
Handwritten character recognition	Handwritten digits (“0”–“9”)	Handwritten English characters (“a”–“z”)	26	Intensities in 28x28 pixel character/digit image
Font character recognition	Handwritten English characters (“a”–“z”)	Font characters (“a”/“A” – “z”/“Z”)	26	Intensities in 28x28 pixel character image
Song genre classification	Song snippets from 10 genres	Song snippets from 7 *different* genres	7	Log-frequency spectrogram over 50ms time windows
Webpage classification	100,000 news articles (Reuters newswire)	Categorized webpages (from DMOZ hierarchy)	2	Bag-of-words with 500 word vocabulary
UseNet article classification	100,000 news articles (Reuters newswire)	Categorized UseNet posts (from “SRAA” dataset)	2	Bag-of-words with 377 word vocabulary

More about Zero-shot learning

- Mark Palatucci, Dean Pomerleau, Geoffrey E. Hinton, Tom M. Mitchell, “Zero-shot Learning with Semantic Output Codes”, NIPS 2009
- Zeynep Akata, Florent Perronnin, Zaid Harchaoui and Cordelia Schmid, “Label-Embedding for Attribute-Based Classification”, CVPR 2013
- Andrea Frome, Greg S. Corrado, Jon Shlens, Samy Bengio, Jeff Dean, Marc'Aurelio Ranzato, Tomas Mikolov, “DeViSE: A Deep Visual-Semantic Embedding Model”, NIPS 2013
- Mohammad Norouzi, Tomas Mikolov, Samy Bengio, Yoram Singer, Jonathon Shlens, Andrea Frome, Greg S. Corrado, Jeffrey Dean, “Zero-Shot Learning by Convex Combination of Semantic Embeddings”, arXiv preprint 2013
- Subhashini Venugopalan, Lisa Anne Hendricks, Marcus Rohrbach, Raymond Mooney, Trevor Darrell, Kate Saenko, “Captioning Images with Diverse Objects”, arXiv preprint 2016