Deep Learning - MAI

Transfer Learning

THEORY

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“Don’t be a hero” - Andrej Karpathy

The Transfer Learning philosophy

Learning from scratch

- Trying to learn from scratch is difficult
  - You have to learn many things before getting to learn complex aspects of your task
- It's easier to learn if you have learnt something beforehand
  - There are some basic things needed to learn anything
  - Learning to "see"

Why Transfer Learning

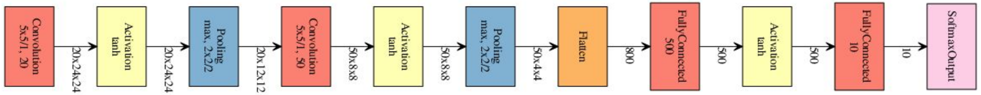
- You can learn faster
  - If I know that much, I’m that much closer to my goal
- You can learn better
  - There is a limited amount of things you can learn from data before getting trapped in spurious patterns.
  - What would you rather learn from your data?

Putting things in perspective

The ImageNet ¿success?

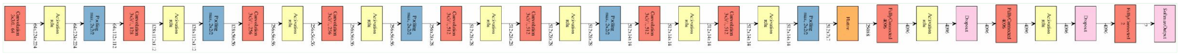
Growing up

- **1998** LeNet-5

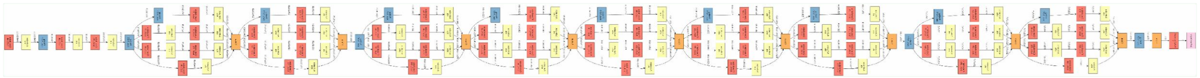


- **2012** AlexNet

- **2014** VGG19



- **2014** GoogLeNet

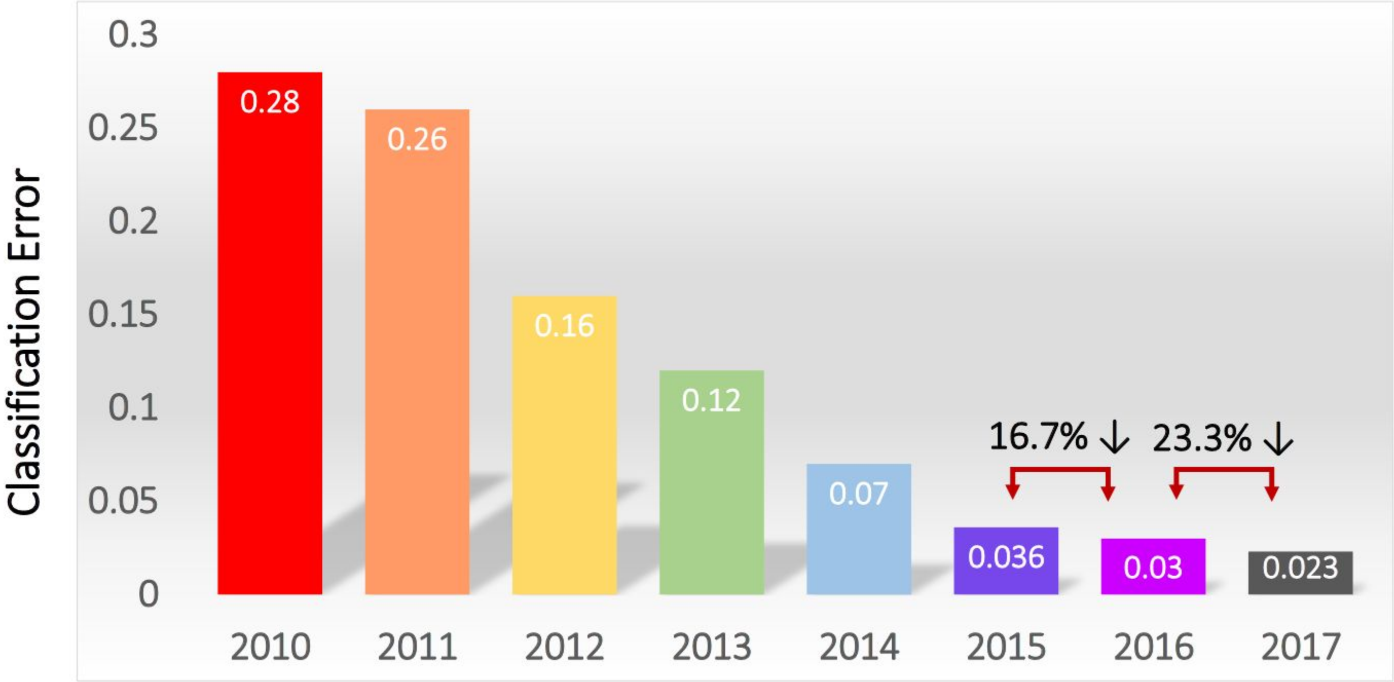


- **2015** Inception-V3

- **2015** ResNet-56

What we get

- We solved ImageNet



What we pay

- Data labeling, transfer & storage
  - 1,000 images per class
- Training cost
  - Money (hardware, energy, salaries)
  - Environmental cost (CO2 emissions)
  - Human effort
    - Highly skilled professionals
    - Architecture design
    - Hyper-parameter fine tuning

HIGH PERFORMANCE ARTIFICIAL INTELLIGENCE

The ImageNet way is no way

- We **cannot** do that for every single problem out there
    - The cost is too high. But more importantly...
- We **do not want to** do that for every single problem out there
    - TL to the rescue
- Transfer learning reduces the requirements on...
    - Data (implicit reuse of data)
    - Cost (reduced training costs)
    - Effort (halfway there)

The essence of Transfer Learning

Learning it's all about generalization

What is learning about?

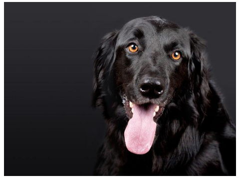










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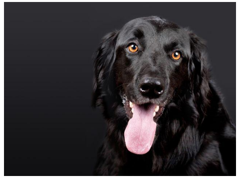
What is learning about?

Train set

Test set



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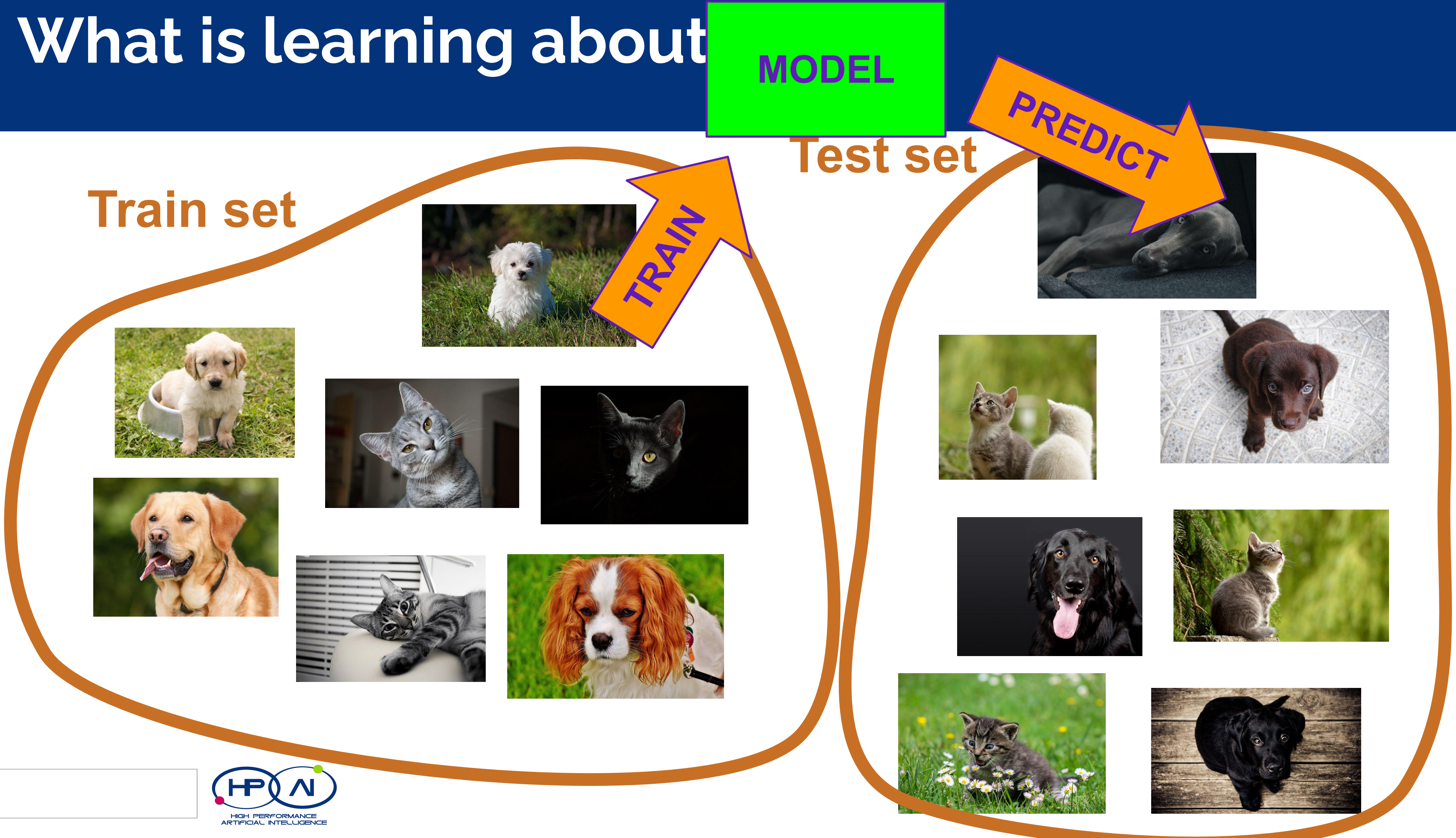
What is learning about



What is learning about

What is the bias here?

Train set

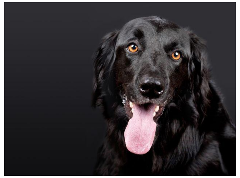






Test set




What is the bias here?

Train set

GREEN BACKGROUND → DOG

HIGH PERFORMANCE ARTIFICIAL INTELLIGENCE

What is the bias here?

Train set







GREEN BACKGROUND → DOG

Train and test sets have different conditional probability distributions

Fixing bias

Train set

Solution?

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Fixing bias

Train set







Solution?

Randomizing ensures that train and test sets have **similar** conditional probability distributions

Fixing bias

Train set

Solution?

Randomizing
train and
lar
cor
distribu

THEY WILL NEVER BE EXACTLY EQUAL

Fixing bias

Train set

More similar means better generalization

Randomizing ensures that train and test sets have **similar** conditional probability distributions

What is learning about?

Generalization between samples from the same source can be (approximately) ensured

Train set

GENERALIZATION

Test set

What about?

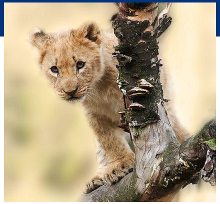
Train set







Test set







What about?

Generalization in this case is less certain
Error is expected to rise
Is it fixable?

Formalizing Transfer Learning

Tasks and Domains

Pan, Sinno Jialin, and Qiang Yang. "A survey on transfer learning." *IEEE Transactions on knowledge and data engineering* 22.10 (2010): 1345-1359.

Formalizing transfer learning

Domain:

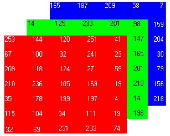
Task:

Formalizing transfer learning

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

- A feature space $\mathcal{X}$

→



≠

"The Elgar Concert Hall at the University of Birmingham for our third conference"

→ Bag of words

→ Content vector

- A marginal probability distribution $P(X), where\ X = \{x_1, \ldots, x_n\} \in \mathcal{X}$

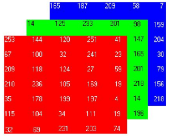
≠

Task:

Formalizing transfer learning

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

- A feature space $\mathcal{X}$

 →  ≠ "The Elgar Concert Hall at the University of Birmingham for our third conference" → Bag of words → Content vector

- A marginal probability distribution $P(X), where\ X = \{x_1, \ldots, x_n\} \in \mathcal{X}$

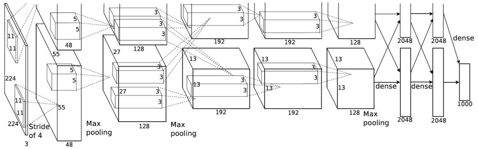
   ≠  

Task: $\mathcal{T} = \{\mathcal{Y}, f(\cdot)\}$

- A label space $\mathcal{Y}$

CAT, DOG ≠ LION, WOLF

- An objective predictive function $f(\cdot) \Leftrightarrow P(y|x)$

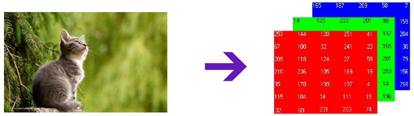


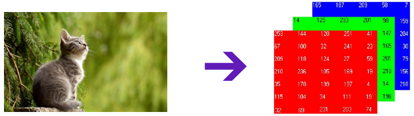
Formalizing transfer learning

Source | **Target**

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

- A feature space $\mathcal{X}$
  - The Same (different)





- A marginal probability distribution $P(X)$
  - Different
  - Similar

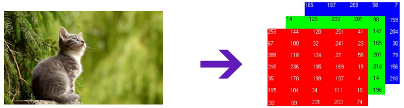
Task: $\mathcal{T} = \{\mathcal{y}, f(\cdot)\}$

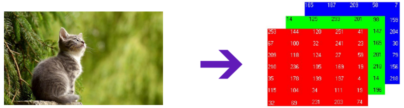
Formalizing transfer learning

Source | **Target**

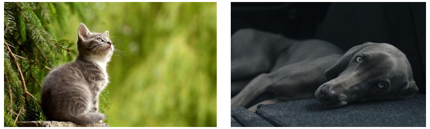
Domain: $\mathcal{D} = \{\mathcal{X}, P(X)\}$

- A feature space $\mathcal{X}$
  - **The Same (different)**





- A marginal probability distribution $P(X)$
  - **Different**
  - **Similar**



Task: $\mathcal{T} = \{\mathcal{Y}, f(\cdot)\}$

- A label space $\mathcal{Y}$
  - **Different**
  - **The same**

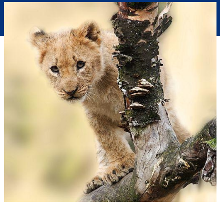
Source	Target
{CAT, DOG}	{LION, WOLF}
{FELINE, CANINE}	{FELINE, CANINE}

- An objective predictive function: $f_S(\cdot)$ (source), $f_T(\cdot)$ (target)
  - **Different (but similar?)**

HIGH PERFORMANCE ARTIFICIAL INTELLIGENCE

What is transfer learning about?

Test set







Train set







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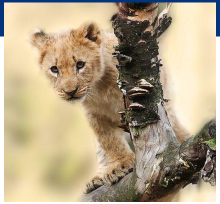
ARTIFICIAL INTELLIGENCE

What is transfer learning about?

Target domain







Source domain







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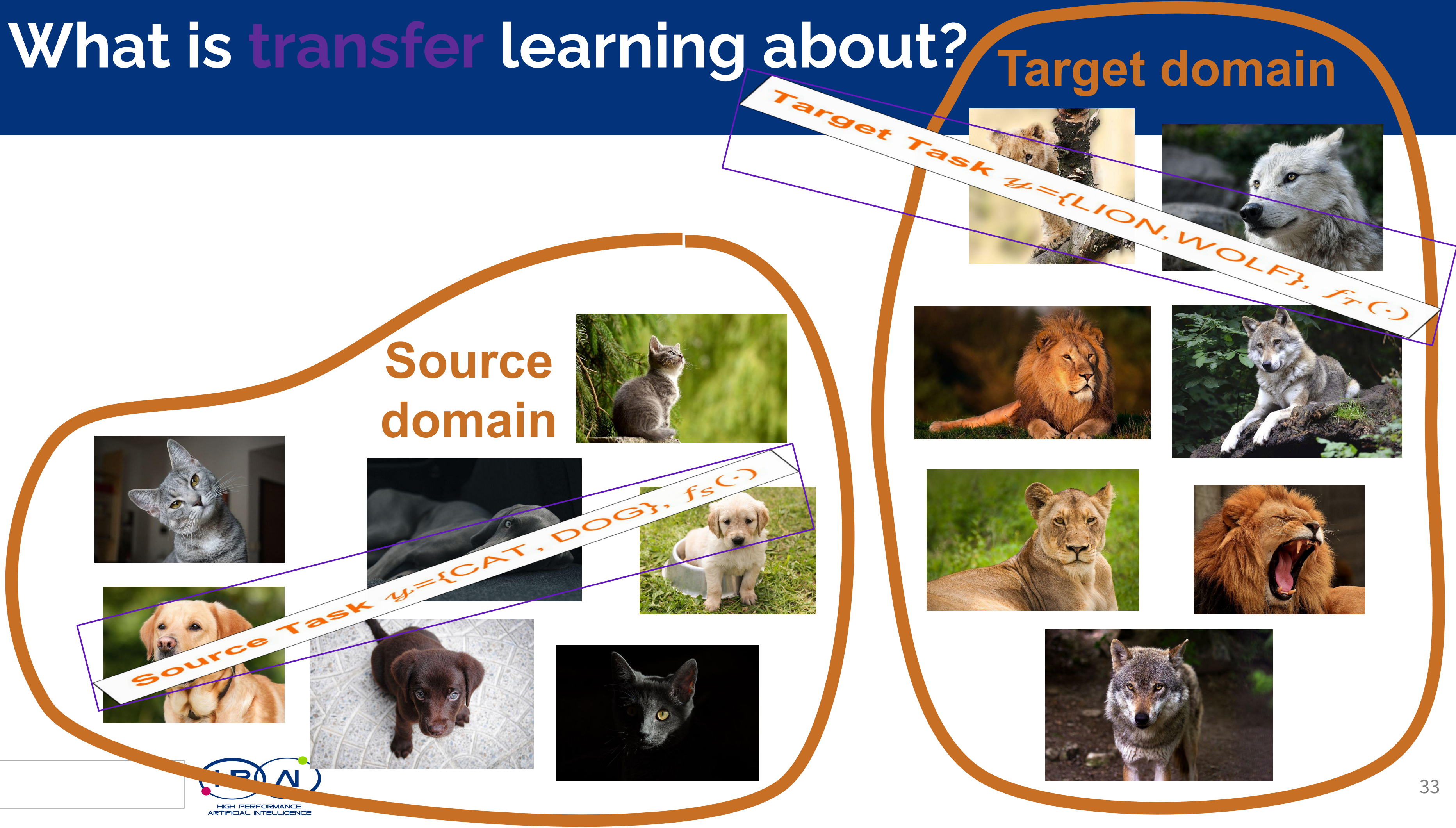
What is transfer learning about?

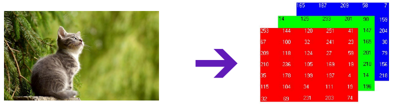


Formalizing transfer learning

Source | Target

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

- A feature space $\mathcal{X}$
  - **The Same (different)**
- A marginal probability distribution $P(X)$
  - **Different**
  - **Similar**



Task: $\mathcal{T} = \{\mathcal{Y}, f(\cdot)\}$

- A label space $\mathcal{Y}$
  - **Different**
  - **The same**

{CAT, DOG} **{FELINE, CANINE}** (Source)

{LION, WOLF} **{FELINE, CANINE}** (Target)

- An objective predictive function $f_S(\cdot)$ $f_T(\cdot)$
  - **Different (but similar?)**

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Formalizing transfer learning

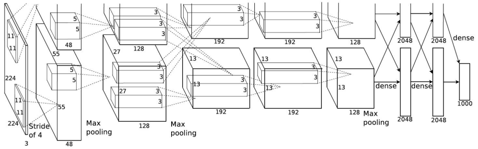
Source

$f_S(\cdot)$

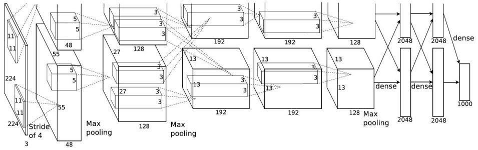
Target

$f_T(\cdot)$

$\hat{f}_S(\cdot)$ =



$\hat{f}_T(\cdot)$ =



- Are they similar?
- Can we just use $\hat{f}_S(\cdot)$ to approximate $f_T(\cdot)$?
- Can we reuse part of it?

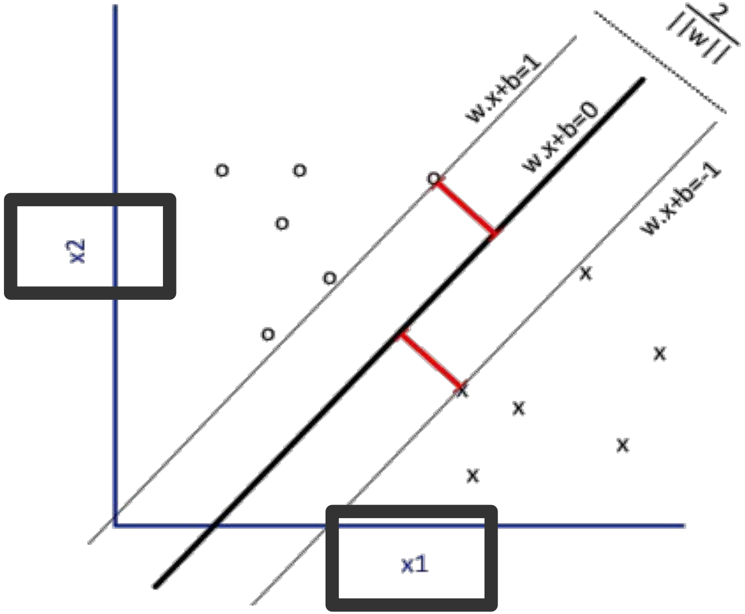
Representation Learning & Classifiers

Learning to describe

A typical classifier

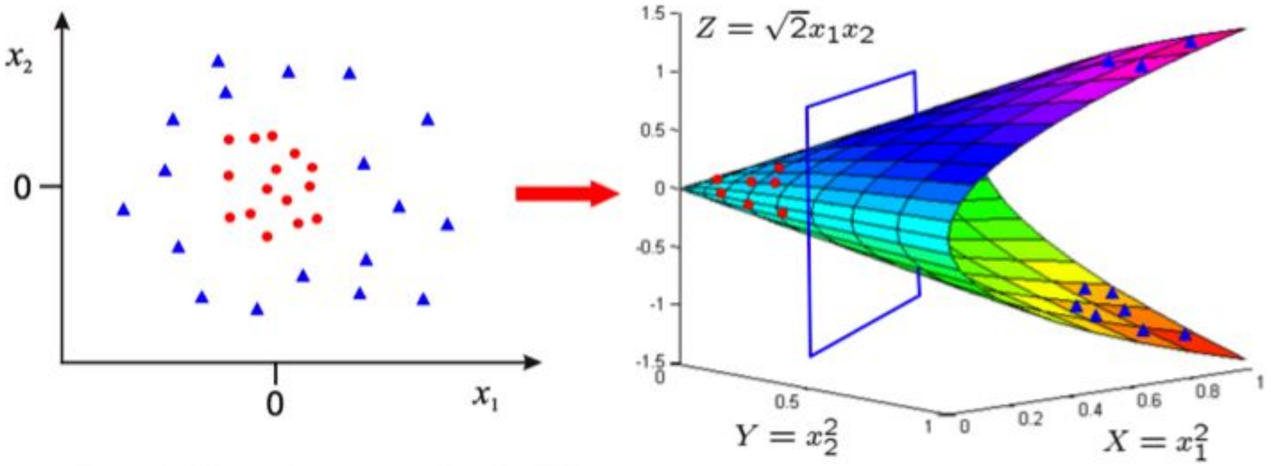
- **Support Vector Machine** (SVM) is just a **classifier** (a very good one).

- SVM find the best boundary separating the data instances into different classes in a **given** feature space.

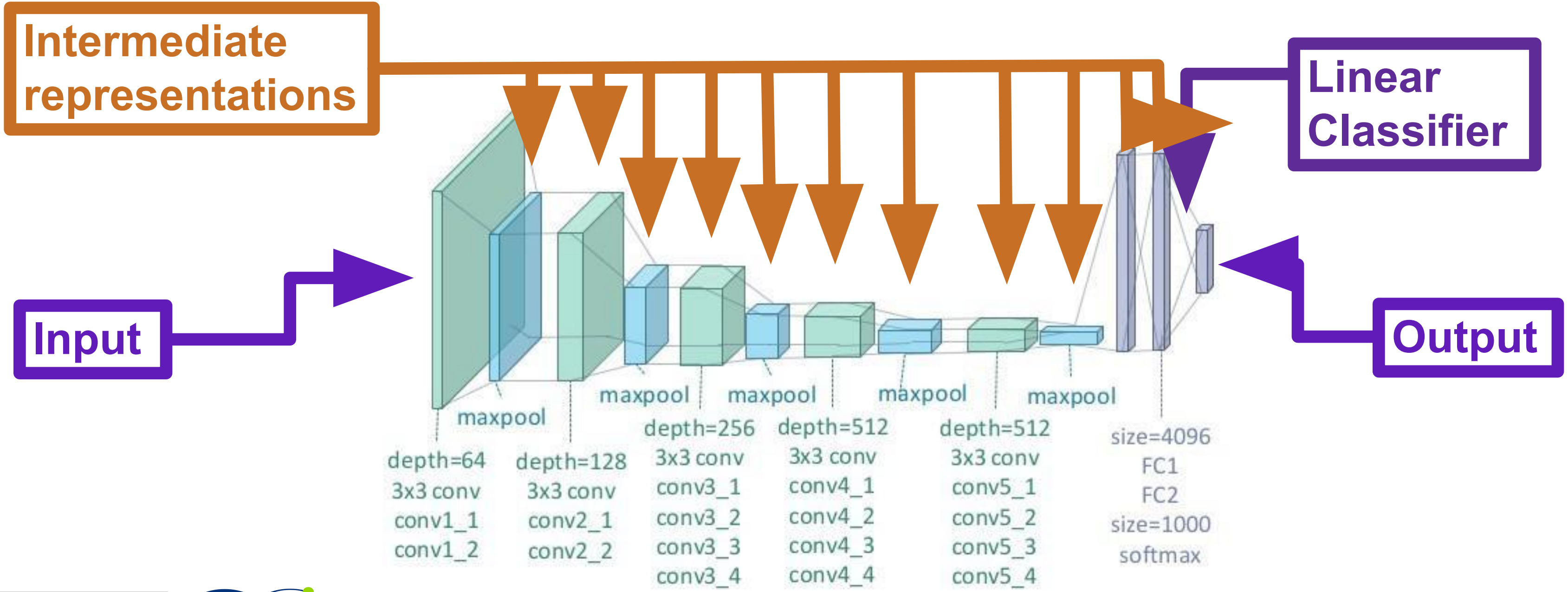


A good classifier

- SVMs using the **kernel trick** can overcome the linear limitation through an **implicit** mapping to a higher dimensional feature space



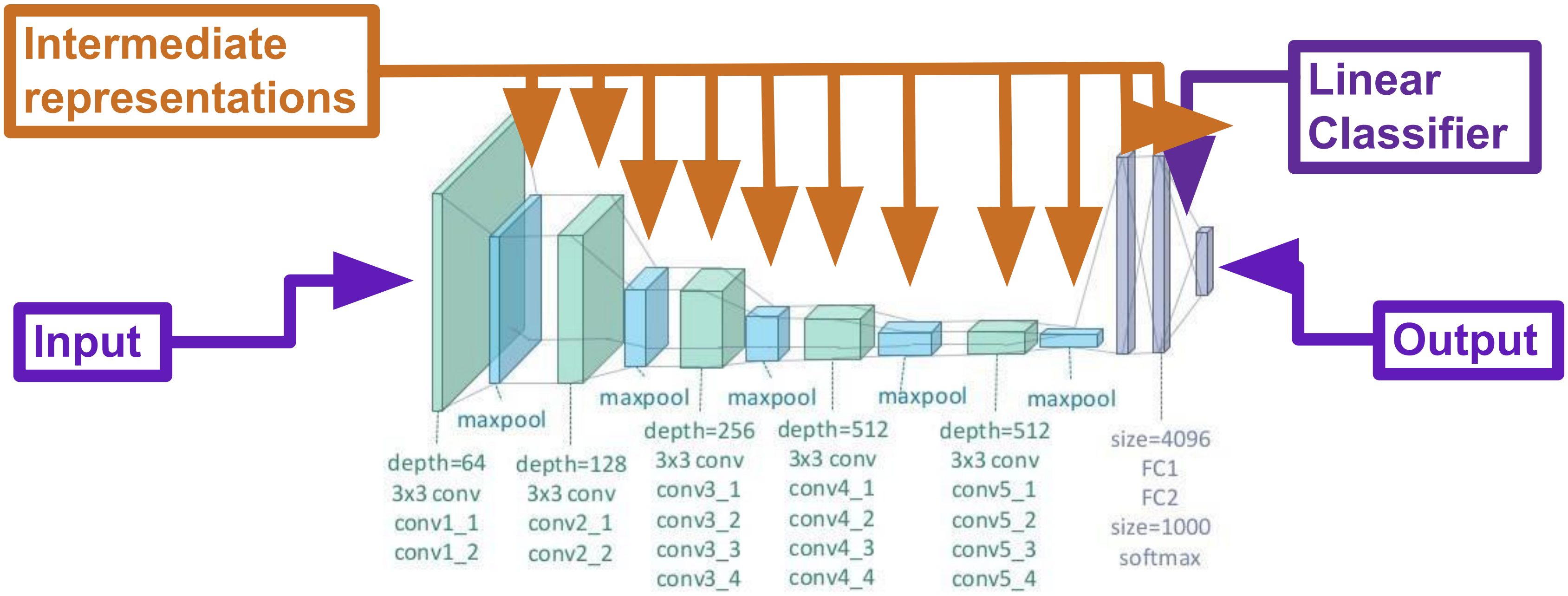
Deep Neural Networks and classifiers



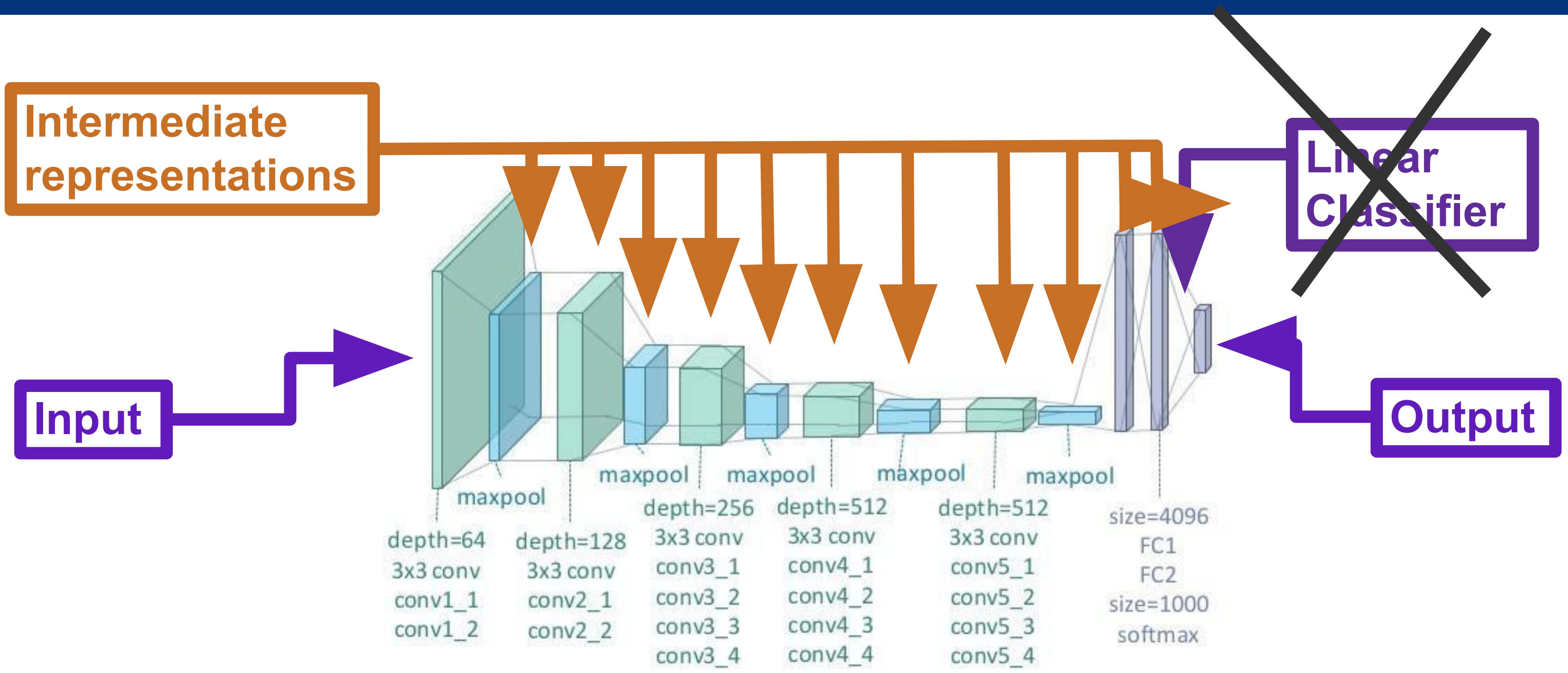
Reusing Deep Representations

Save the Earth - Reuse DNNs

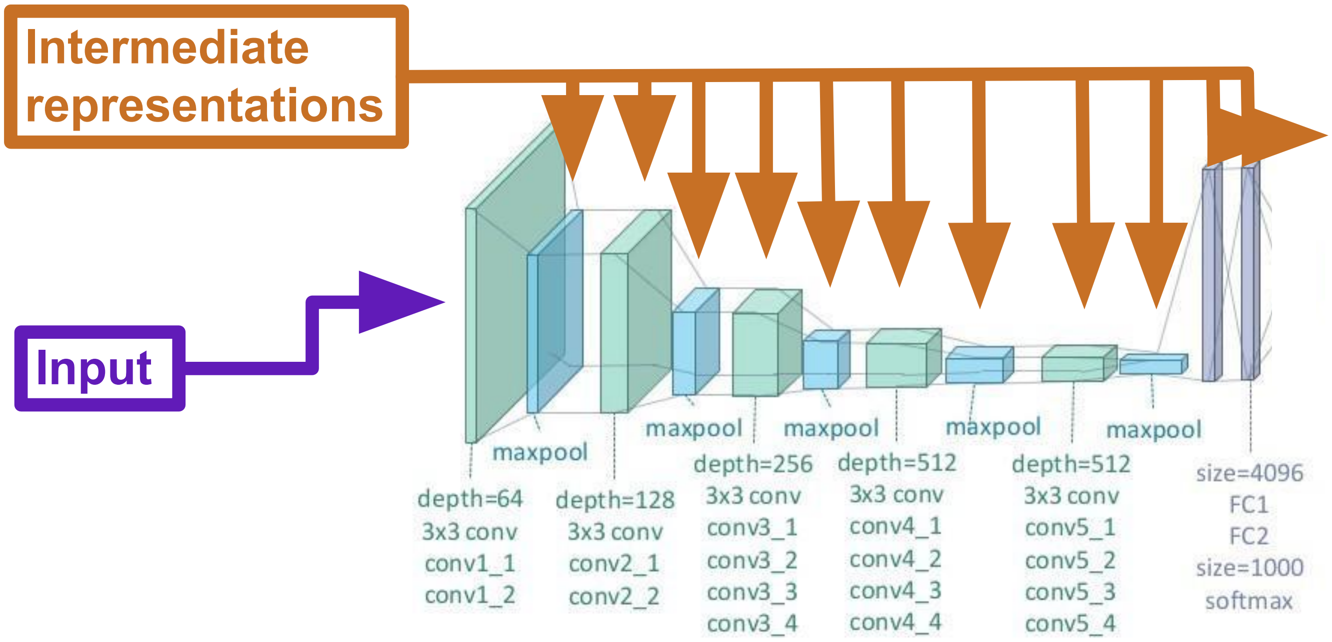
What can be saved?



What can be saved?



Feature extraction



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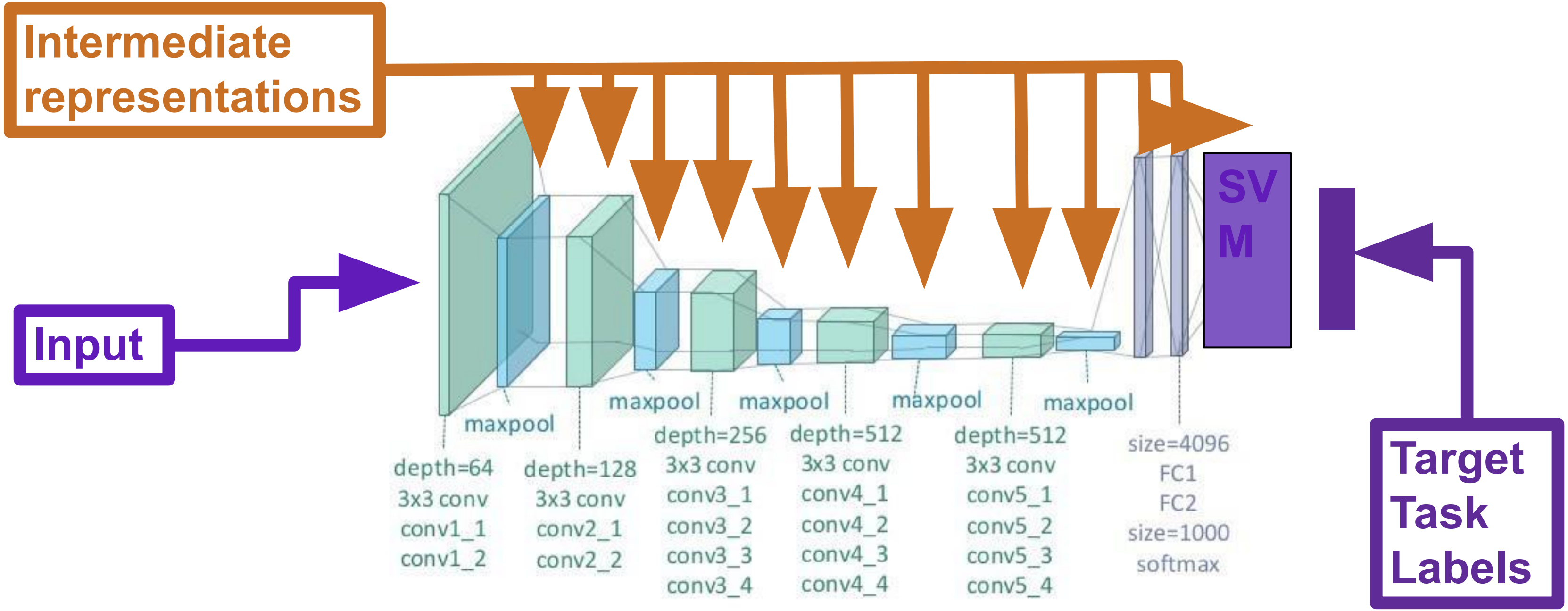
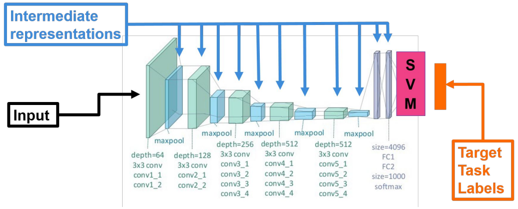
Feature extraction



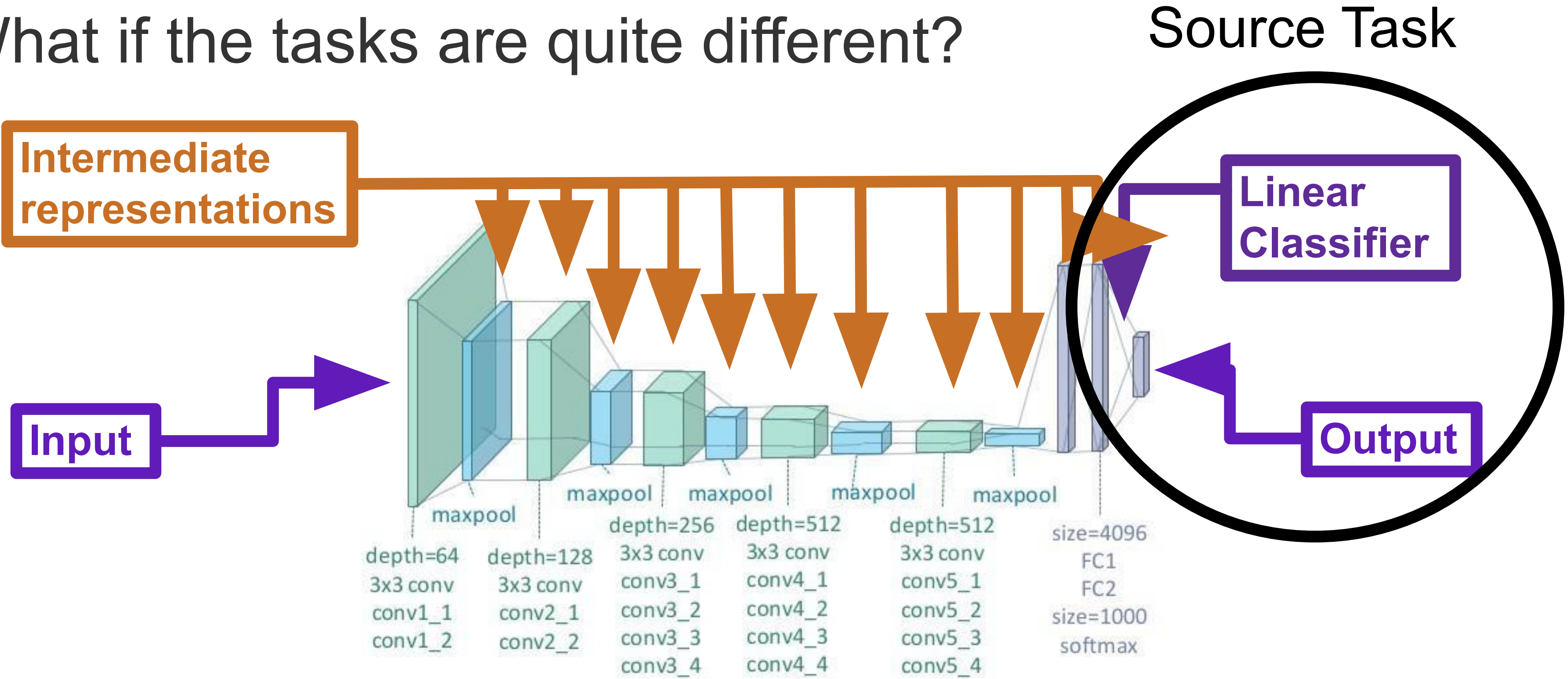
Reuse All

- DNN last layer features + SVM
  - Feature extraction
  - Similar task and domain

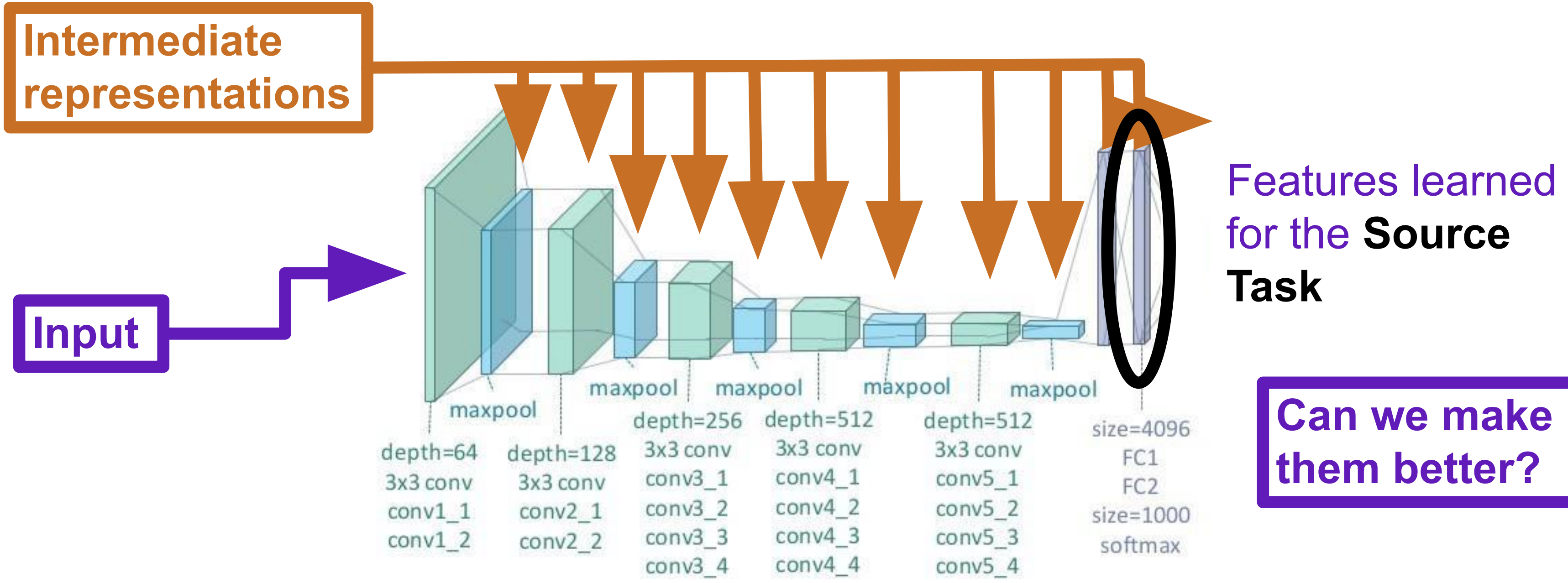


Fine tuning

What if the tasks are quite different?

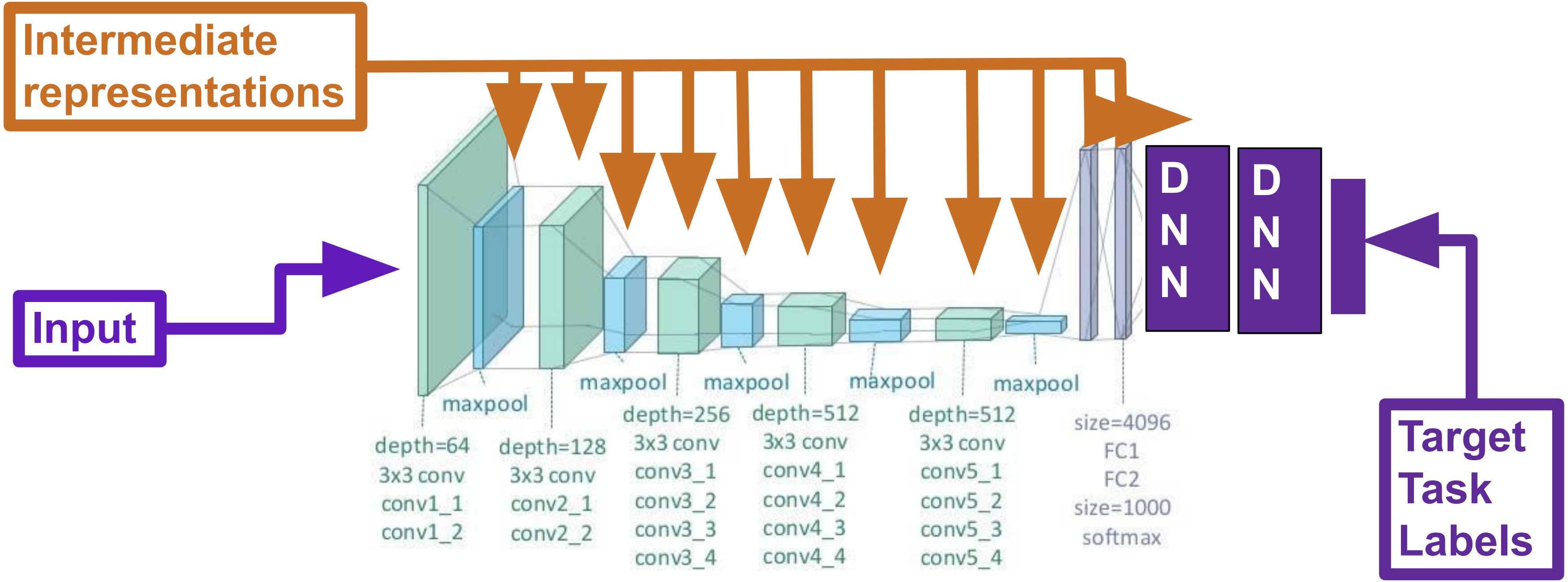


Fine tuning

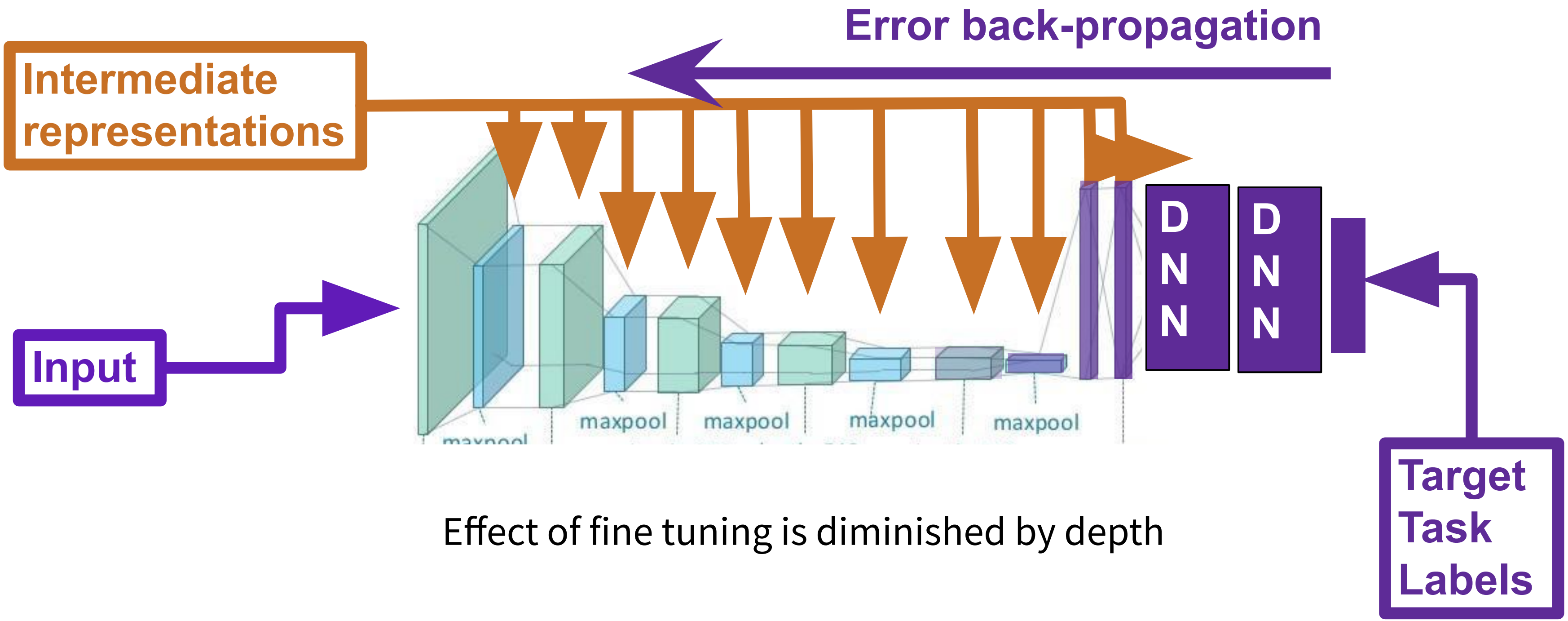


Can we make them better?

Fine tuning

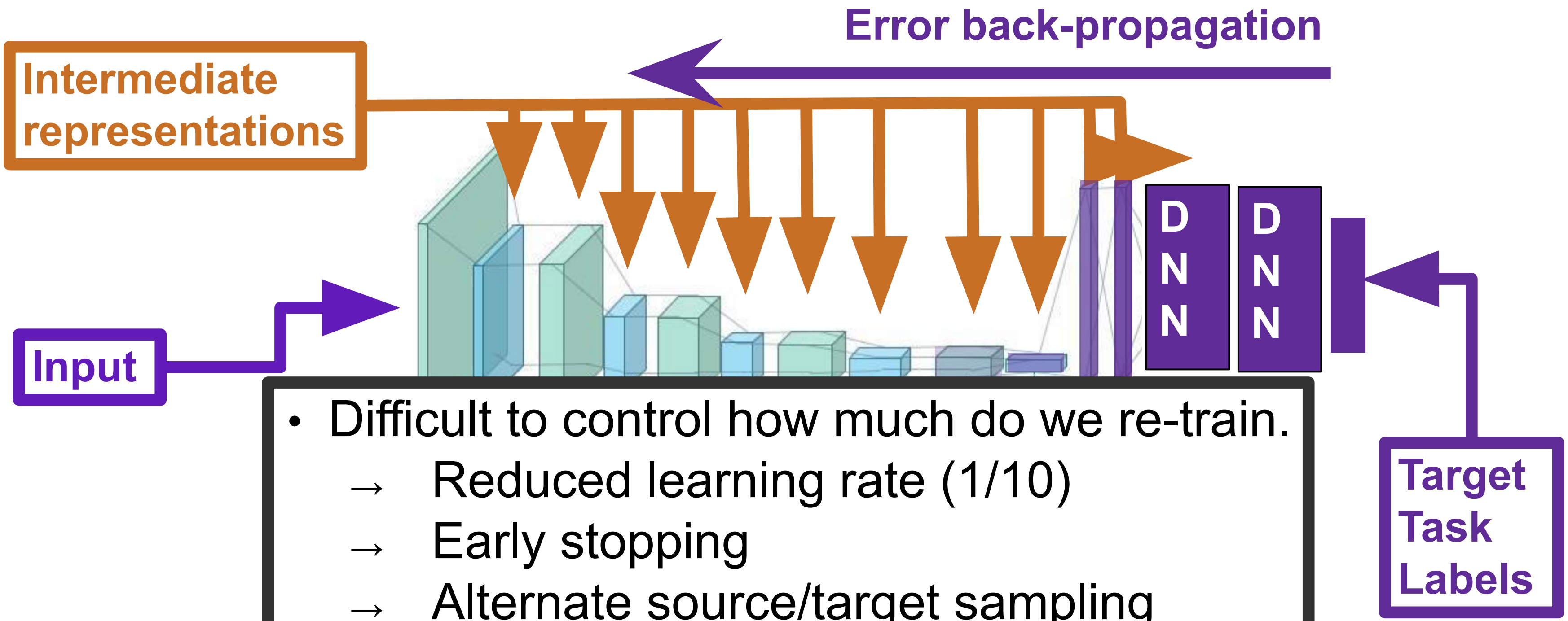

Intermediate representations
Input
maxpool
maxpool
maxpool
maxpool
maxpool
depth=64
3x3 conv
conv1_1
conv1_2
depth=128
3x3 conv
conv2_1
conv2_2
depth=256
3x3 conv
conv3_1
conv3_2
conv3_3
conv3_4
depth=512
3x3 conv
conv4_1
conv4_2
conv4_3
conv4_4
depth=512
3x3 conv
conv5_1
conv5_2
conv5_3
conv5_4
size=4096
FC1
FC2
size=1000
softmax
DNN
DNN
Target Task Labels

Fine tuning



Effect of fine tuning is diminished by depth

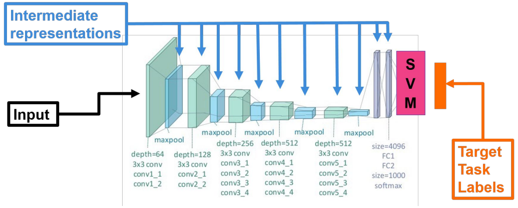
Fine tuning



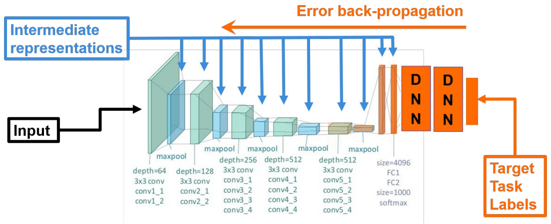
- Difficult to control how much do we re-train.
  - → Reduced learning rate (1/10)
  - → Early stopping
  - → Alternate source/target sampling

Retrain

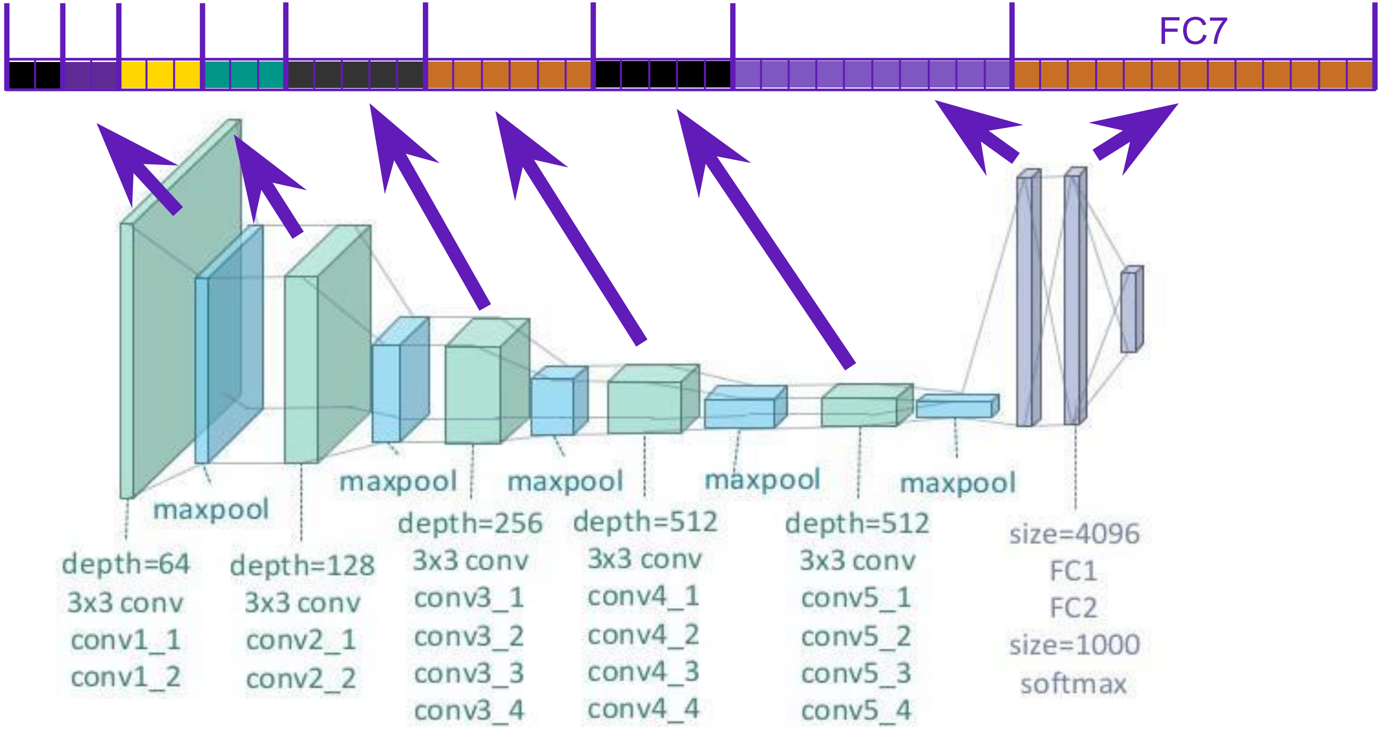
- DNN last layer features + SVM
  - Feature extraction
  - Similar task and domain



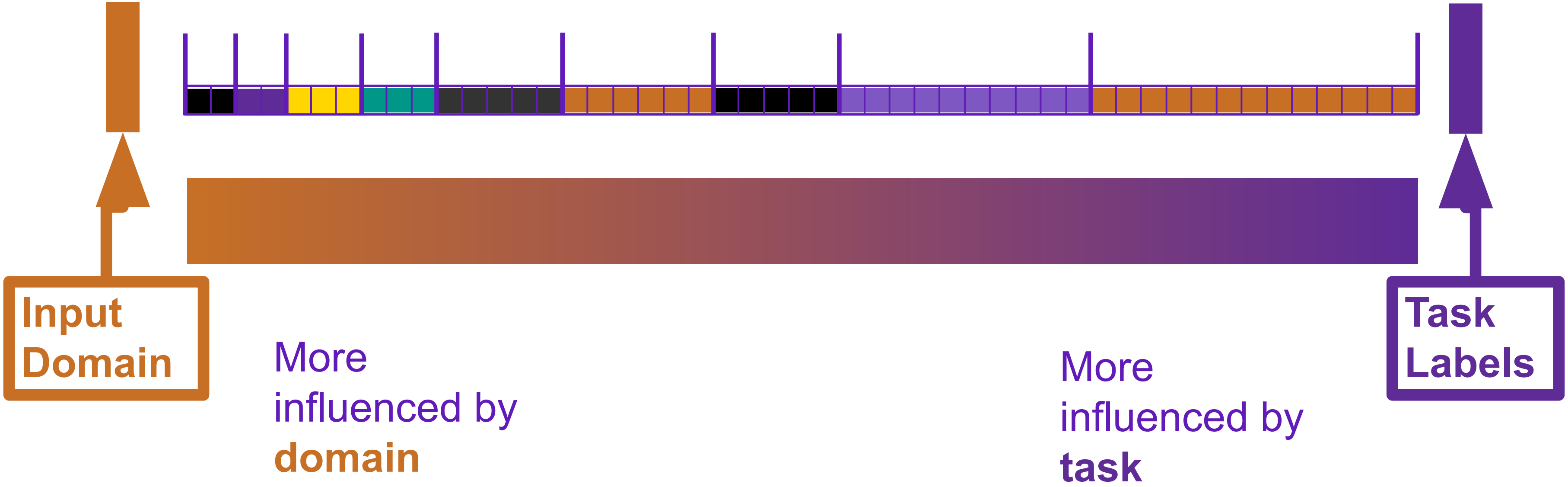
- Train one or several NN layers + pre-trained layers
  - Fine tuning
  - Data volume



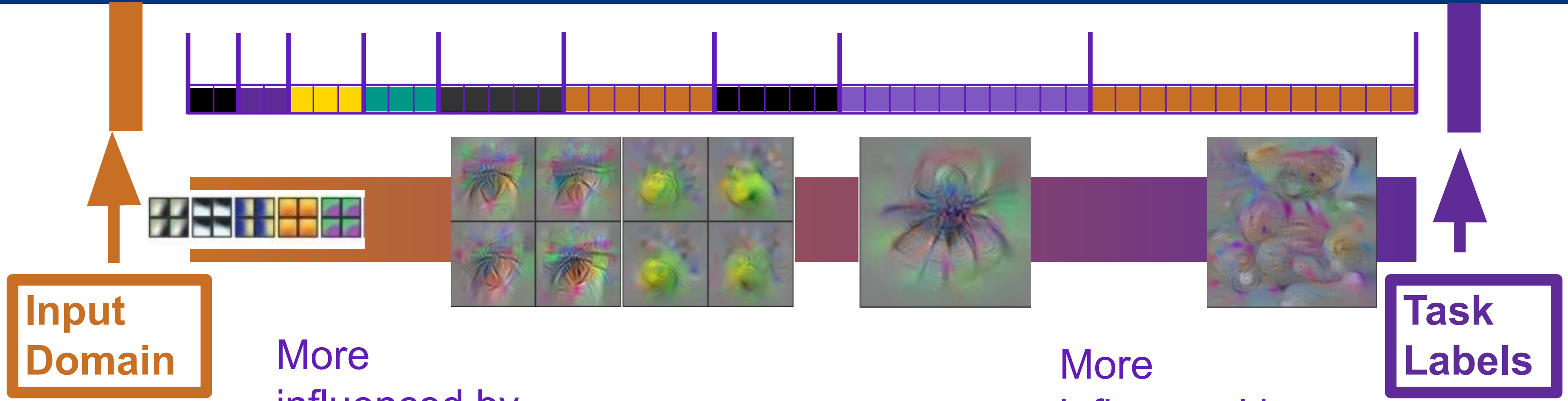
Knowledge inside DNN



Knowledge inside DNN



Knowledge inside DNN



More influenced by **domain**

Simple features

More influenced by **task**

Complex features

Visualizations from: Yosinski, Jason, et al. "Understanding neural networks through deep visualization." *arXiv preprint arXiv:1506.06579* (2015).

Fine Tuning

To improve, to remember, to forget

The choices in fine tuning

- Reuse and **freeze**
  - Use source status
  - “Its good as it is”
- Reuse and **fine tune**
  - Start from source status, adjust with target
  - “Its a good starting point”
- **Random** init
  - Reinitialize weights randomly, train with target only
  - “Its pretty much useless”

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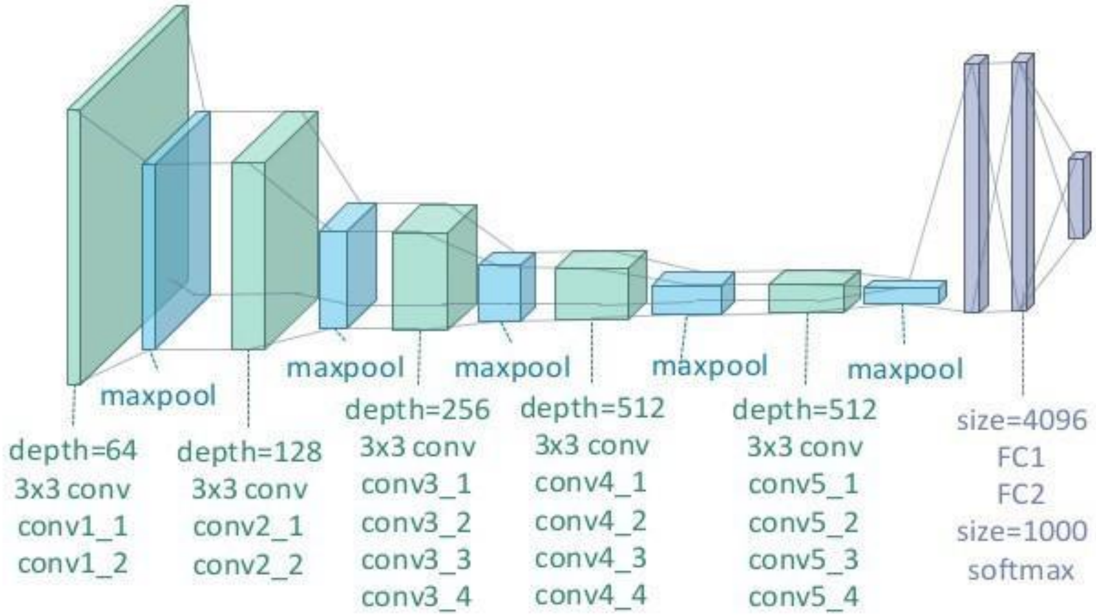
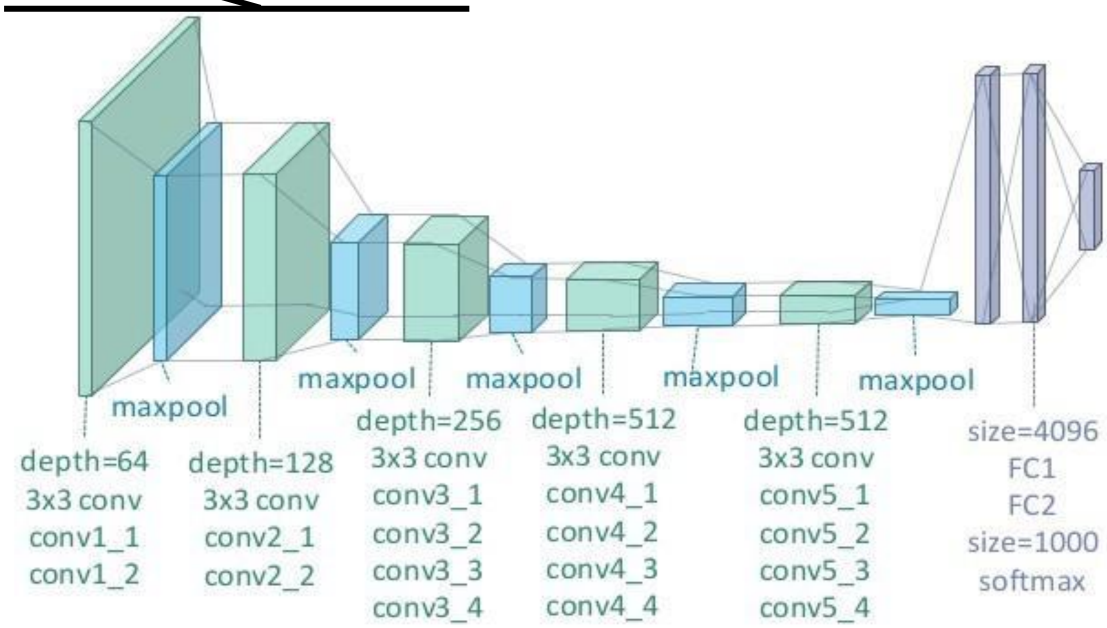
The order of fine tuning

Freeze **Fine tune** **Random**



The order of fine tuning

Freeze Layers which are pretty stable and universal
Increase with source-target similarity



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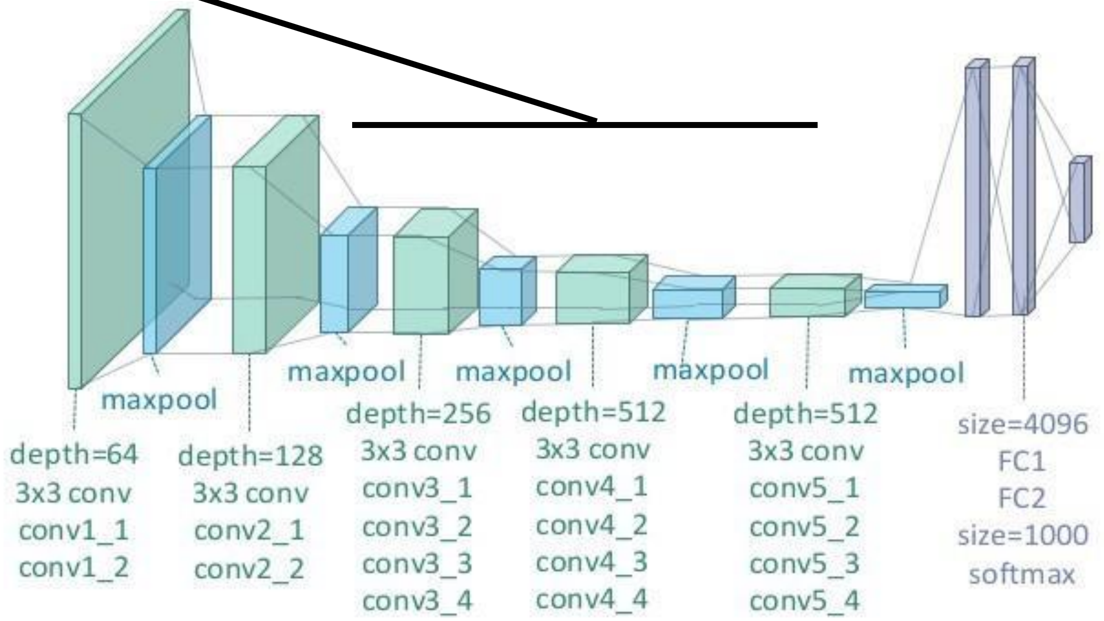
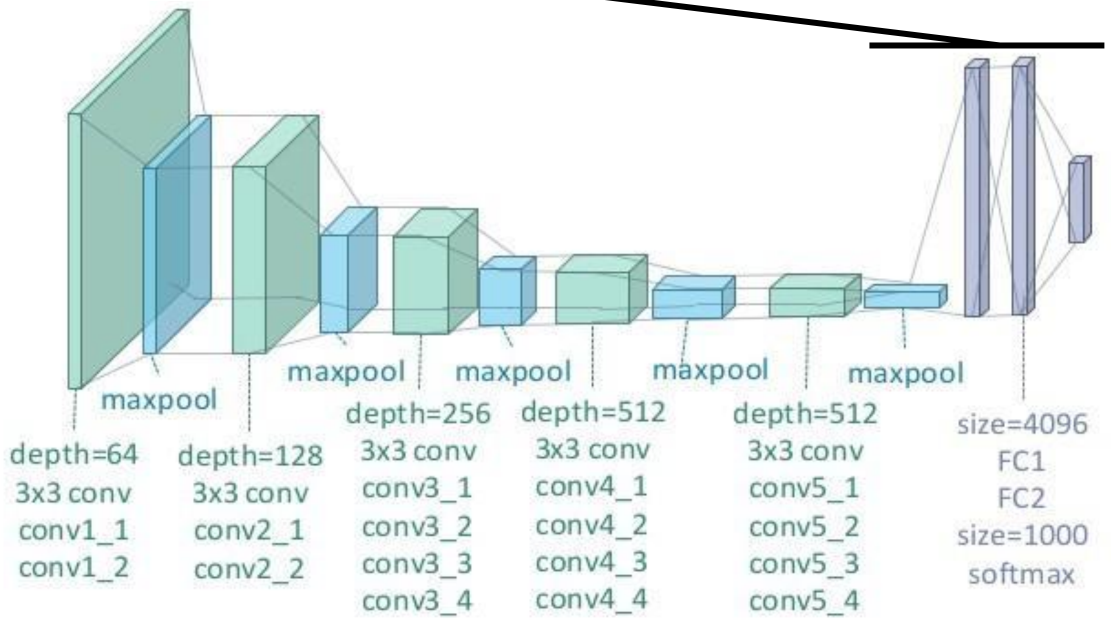
The order of fine tuning

Fine tune Layers which are pretty similar but improvable
Increase with source-target similarity & data volume



The order of fine tuning

Random Layers which are pretty dissimilar
Increase with source-target dissimilarity & data volume



Trade-off of fine tuning

- Reuse and **freeze**
  - Remove parameters for target to learn (needs data but allows focus)
  - Adds noise
- Reuse and **fine tune**
  - Allows to focus learning (requires data)
  - Adds bias
- **Random** init
  - Again, from the top (cost, cost, cost)
  - Tailor made for target

Feature Extraction

To improve, to remember, to forget

Factors deep representations quality

- Source task
  - Total volume
  - Class variety
- Target task
  - Source-target similarity
- Model
  - Capacity
  - Accuracy

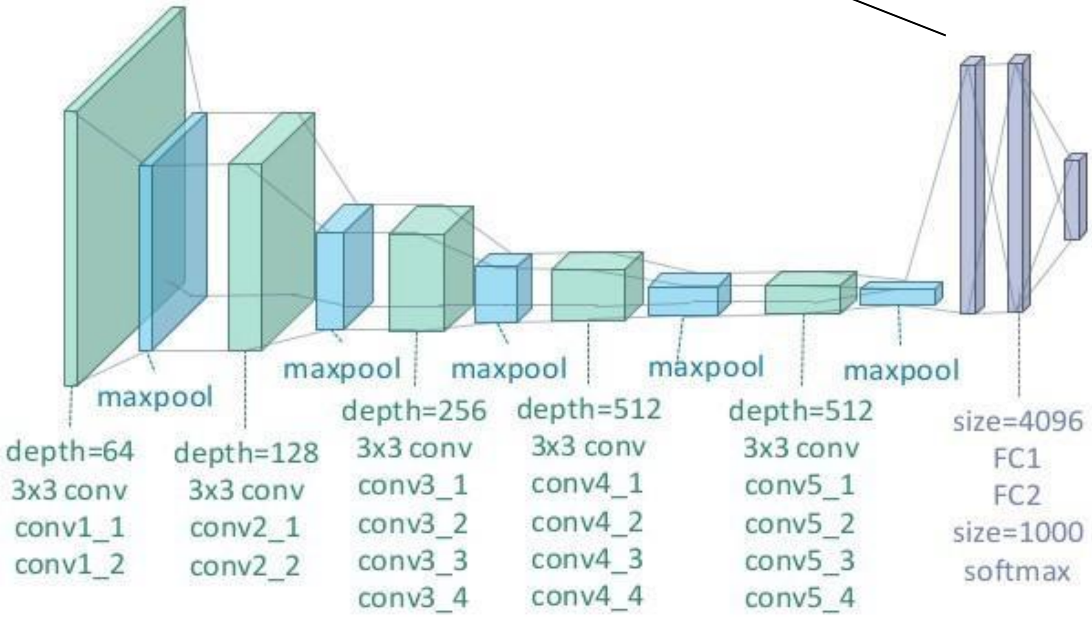
Factors deep representations quality

- Source task
  - Total volume
  - Class variety
- Target task
  - Source-target similarity
- Model
  - Capacity
  - Accuracy

If you have all of this, feature extraction plus a classifier will get you close to state-of-the-art

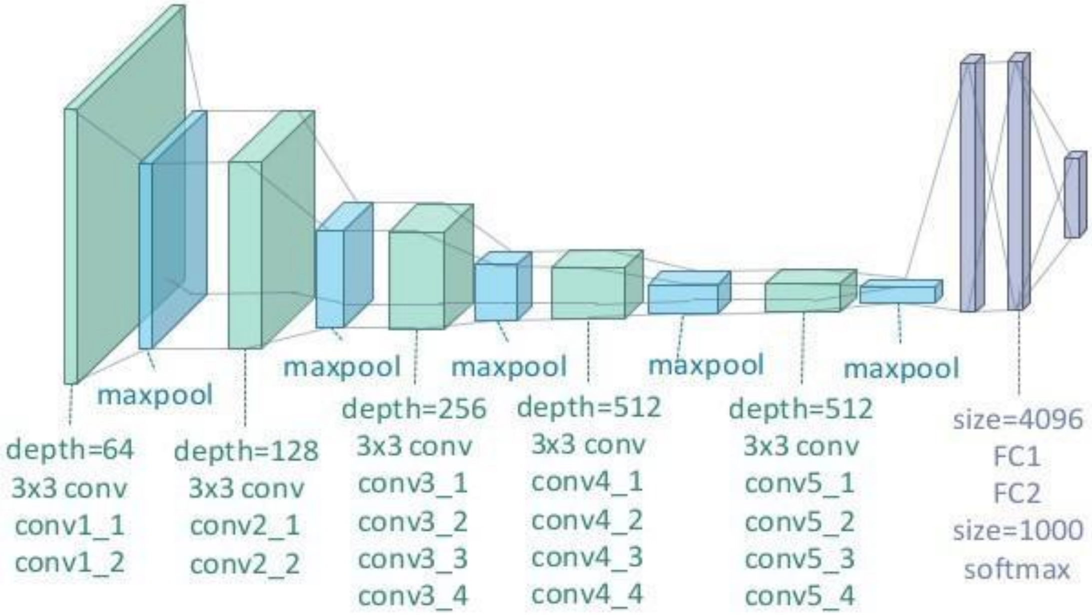
Which layers to use?

- If source & target task are VERY similar
  use the “classifier” layers



Which layers to use?

- If source & target task are NOT very similar
  broaden the scope



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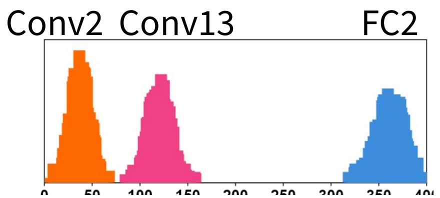
Feature extraction normalization

- When doing feature extraction for a regular classifier (e.g., SVM) each feature is assumed to be i.i.d. (not even close!)
- Beware of size
  - FC layers have lots of activations
  - Conv layers activations are spatially dependent
- Beware of scale
  - Different layers activate with different strength
- Default solution: L2-norm (by layer)
  - Does not fix scale (careful if mixing layers!)

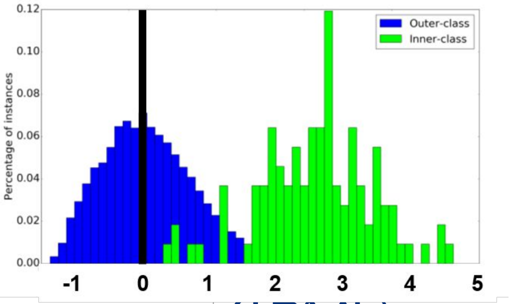
VGG16	*Convs*	*FCs*
# Layers:	14	2
Activations:	33%	66%

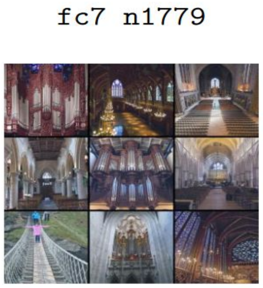


Advanced feature normalization

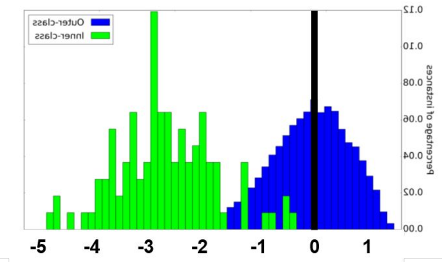
- Normalizing features considering the target
  - Feature standardization (vertically instead of horizontally)
- For each feature..
  - Compute mean and std dev. on *target* training set
  - Normalize feature-wise to zero mean, one std dev.
  - Features are adapted to *target domain*

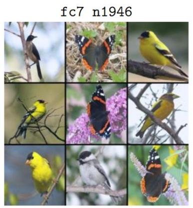
Best for multi-layer feature extraction





Cloister





Gadwall Brown Pelican White Pelican Heermann Gull

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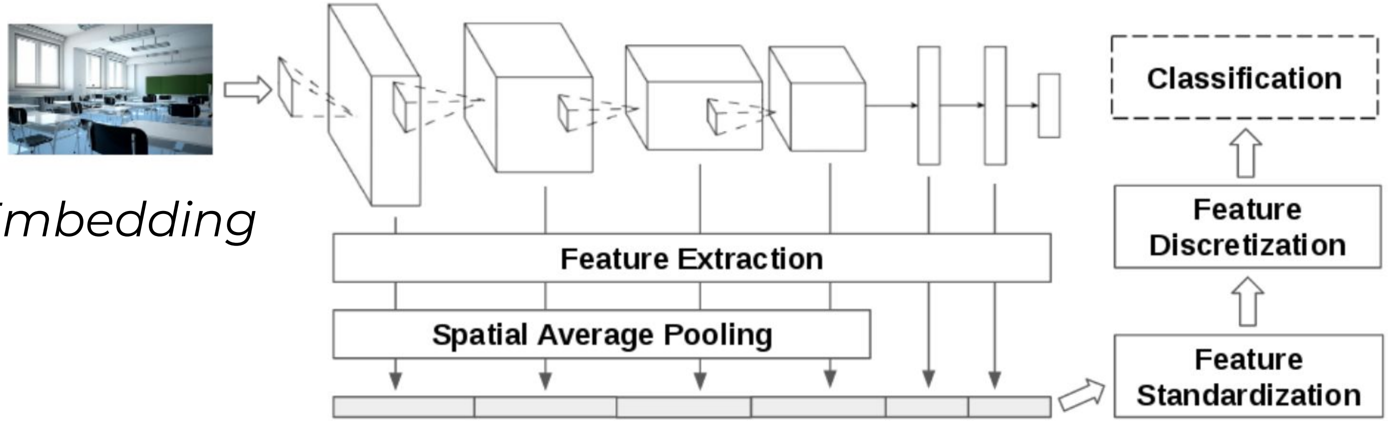
Advanced feature normalization

- Dimensionality of extracted features is an issue (12K in VGG16)
- Removing complexity without losing expressivity
  - Discretizing the space (-1,0,1)

Full-Network Embedding

(FNE)



Feature extraction in action

- High similarity source - target

Network pre-trained on **Places2** for mit67 and on **ImageNet** for the rest.

Dataset	mit67	cub200	flowers102	cats-dogs	sdogs	caltech101	food101	textures	wood
Baseline fc6	80.0	65.8	89.5	89.3	78.0	91.4±0.6	61.4±0.2	69.6	70.8±6.6
Baseline fc7	81.7	63.2	87.0	89.6	79.3	89.7±0.3	59.1±0.6	69.0	68.9 ±6.8
Full-network	83.6	65.5	93.3	89.2	78.8	91.4±0.6	67.0±0.7	73.0	74.1±6.9
SotA	86.9 [5]	92.3 [10]	97.0 [5]	91.6 [6]	90.3 [5]	93.4 [31]	77.4 [4]	75.5 [17]	- -
ED	✓	✓	✓	✗	✓	✗	✗	✗	-
FT	✓	✓	✓	✓	✓	✓	✓	✗	-

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ED	✓	✓	✓	✗	✓	✗	✗	✗	-
FT	✓	✓	✓	✓	✓	✓	✓	✗	-

+2.9
+4.2

Task similarity makes single layer l2-norm competitive

Feature extraction in action

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ED	✓	✓	✓	✗	✓	✗	✗	✗	-
FT	✓	✓	✓	✓	✓	✓	✓	✗	-

+7.9

Data (external or not) can **make fine tuning worth the COST**

Feature extraction in action

- Low similarity source - target (*most real-world scenario!*)

Network pre-trained on **ImageNet** for mit67 and on **Places2** for the rest.

Dataset	mit67	cub200	flowers102	cats-dogs	caltech101	textures	wood
Baseline fc7	72.2	23.6	73.3	38.7	72.0	55.8	65.3
Full-network	75.5	35.5	88.7	56.2	80.0	65.1	74.0
	+3.3	+11.9	+15.4	+17.5	+8.0	+9.3	+10.6

Data (external or not) makes fine tuning worth the COST

Key takeaways

- If possible, always use a pre-trained net
  - Don’t be a hero
- Consider the gradient of representations
  - From data to task
- Always analyze
  - Source/Target similarity
  - Data availability

Key takeaways

- Fine tune if possible
  - Freeze from the bottom
  - Fine tune the middle
  - Retrain from random the top
- Feature extraction
  - Must-do baseline (cheap and easy!)
  - Only feasible approach if data volume is short

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