Deep Learning - MAI

Transfer Learning

THEORY

Dario Garcia Gasulla
dario.garcia@bsc.es

“Don’t be a hero” - Andrej Karpathy

The Transfer Learning philosophy

Learning from scratch

- Trying to learn from scratch is difficult and arduous
  - You have to learn many fundamental things before getting to learn complex aspects of your task
- It's easier to learn if you already know something beforehand
  - There are some basic things needed to learn anything
  - In image processing, learning to "*see*": Characterize images based on fundamental visual features

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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?

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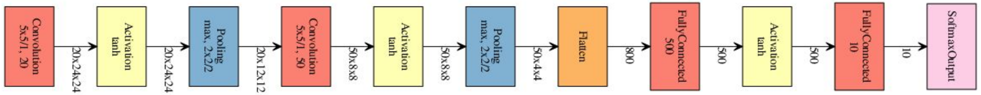
Putting things in perspective

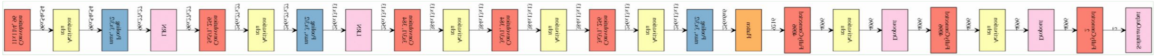
The ImageNet ¿success?

Growing up

- **1998** LeNet-5

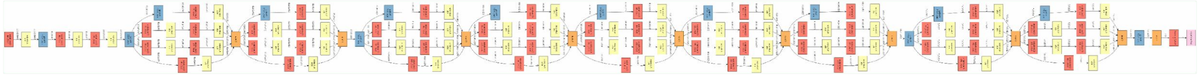


- **2012** AlexNet



- **2014** VGG19

- **2014** GoogLeNet

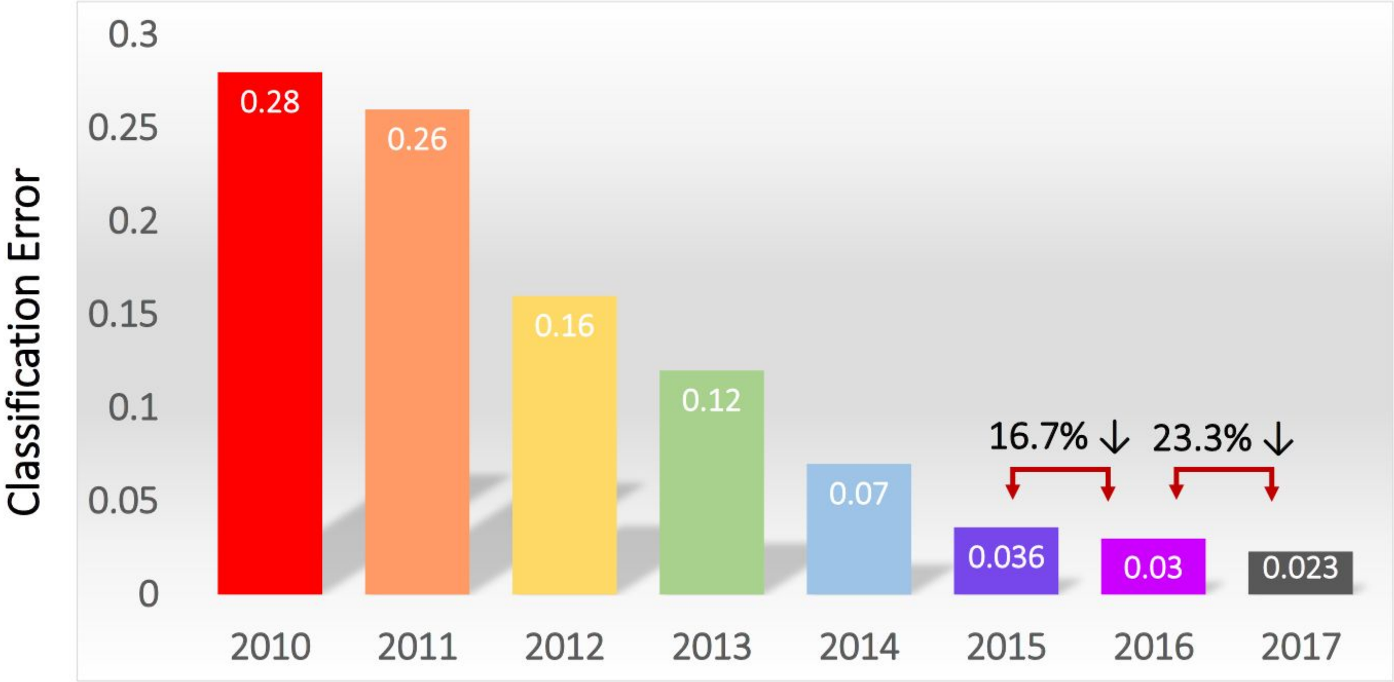


- **2015** Inception-V3

- **2015** ResNet-56

What we get

- We solved ImageNet



What we pay

- Data labeling, transfer & storage
  - e.g., 1,000 images per class
- Training cost
  - Money (hardware, energy, salaries)
  - Environmental cost (CO_2 emissions)
  - Human effort
    - Highly skilled professionals
    - Architecture design
    - Hyper-parameter fine tuning

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The ImageNet way is no way

- We **cannot** do that for every single problem out there
  - The cost is too high. But more importantly...

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 (faster convergence)
  - Effort (initial design & parametrization)

The essence of Transfer Learning

Learning it's all about generalization

What is learning about?

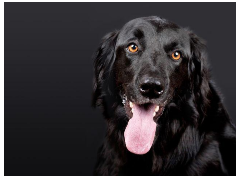













What is learning about?

Train set

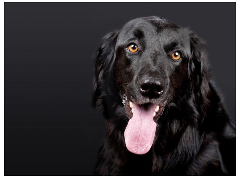




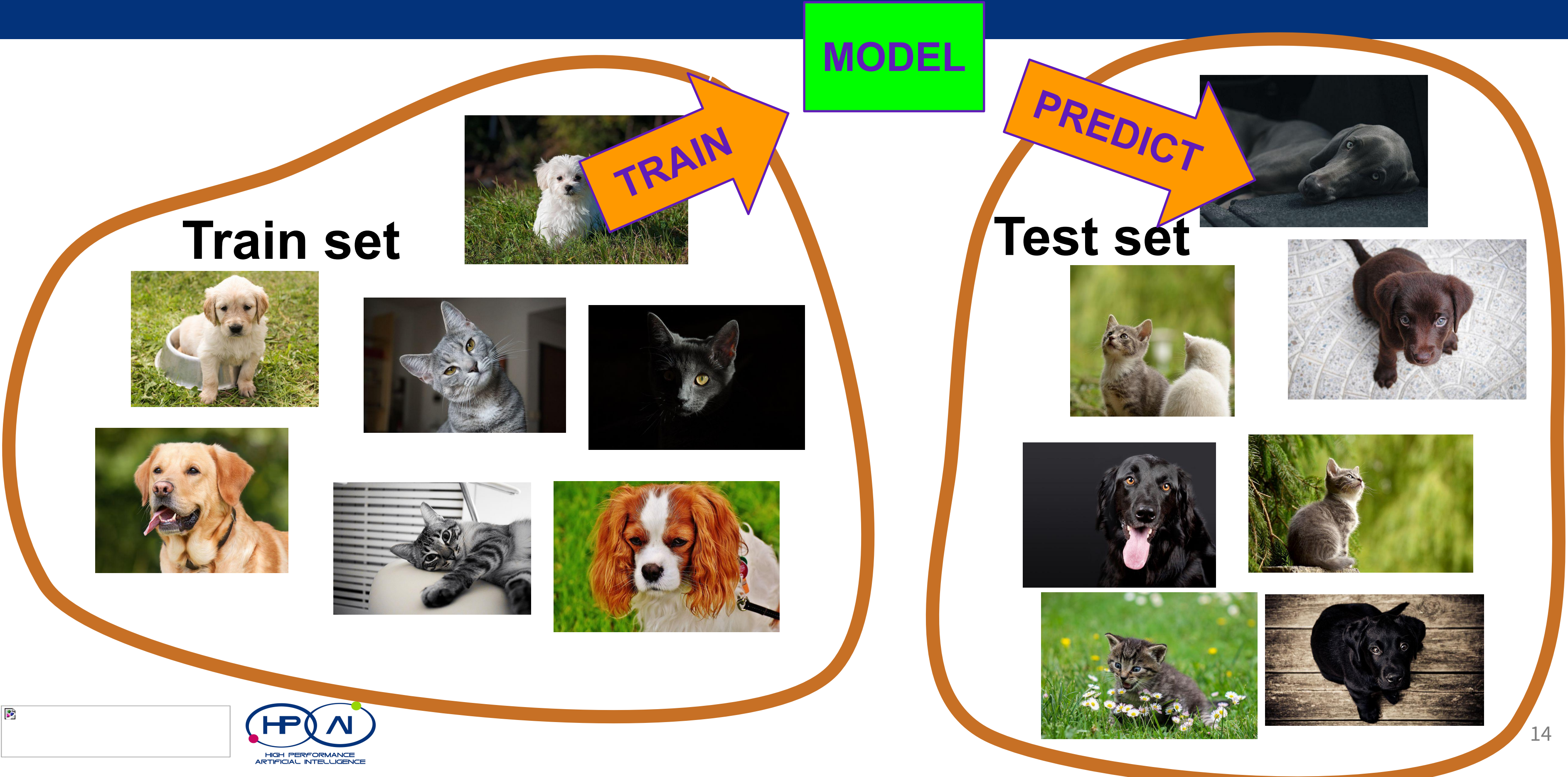


Test set

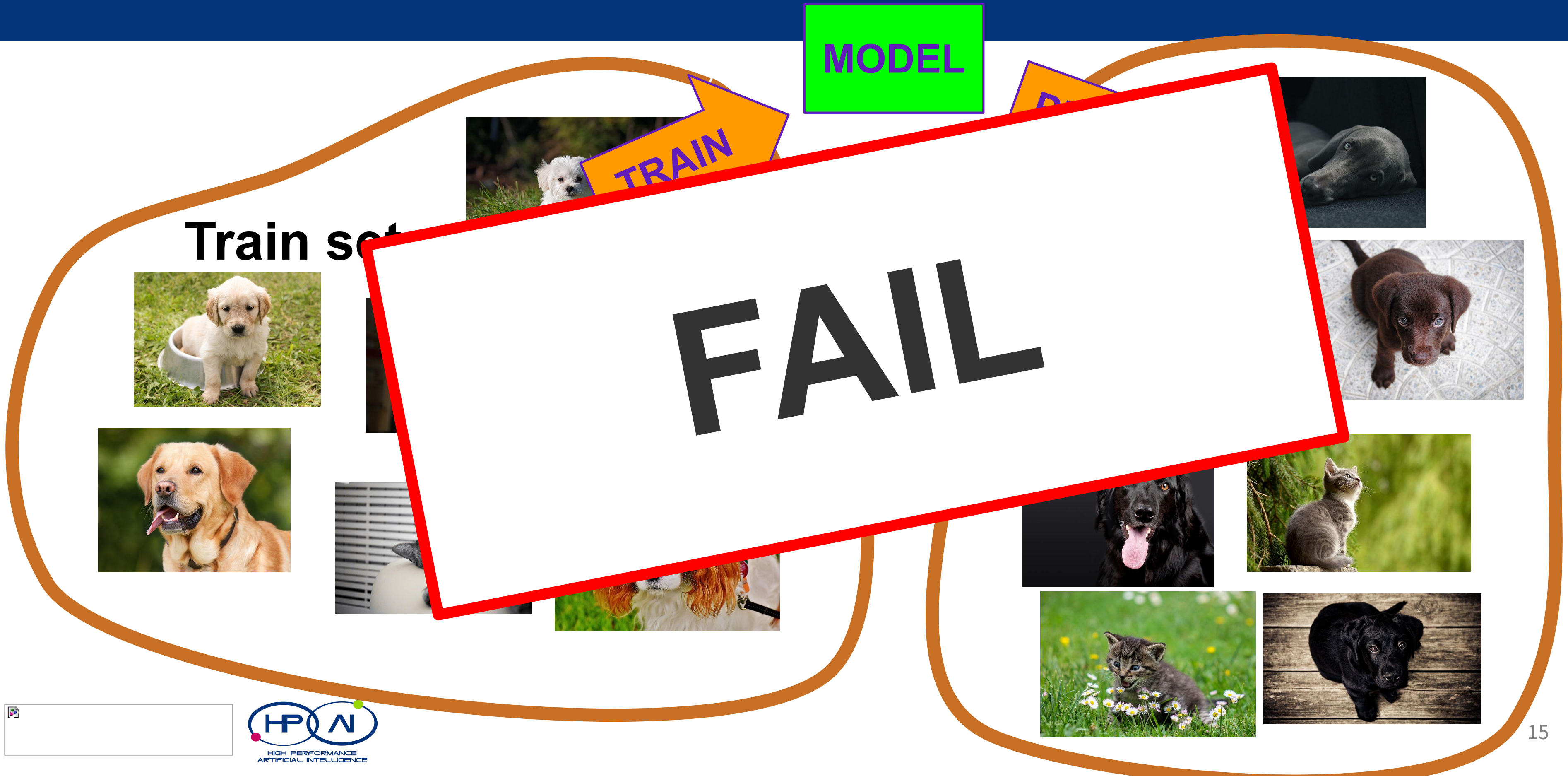



What is learning about?



What is learning about?



What is the bias here?

Train set

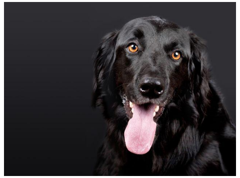






Test set




What is the bias here?

Train set

GREEN BACKGROUND → DOG

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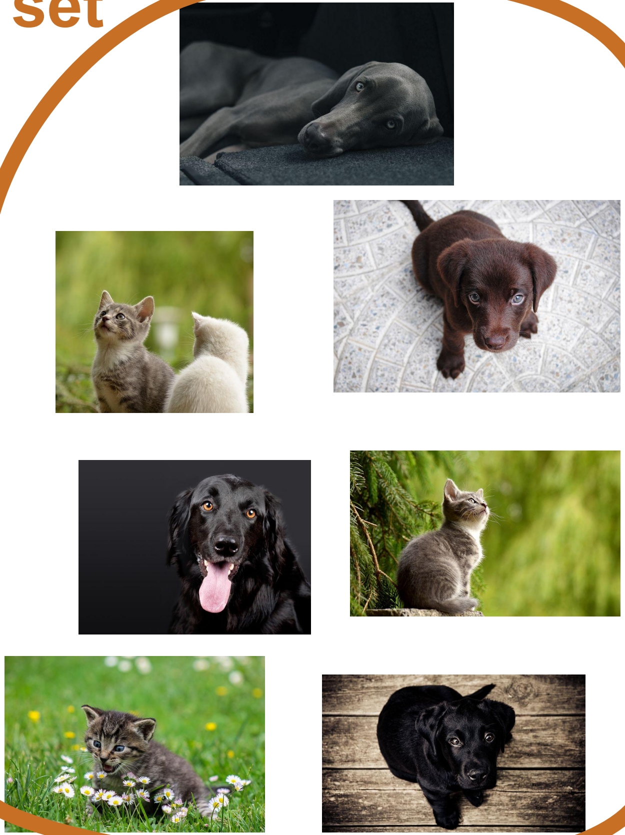
What is the bias here?

CAT

GREEN BACKGROUND

Test set



What is the bias here?

Train set

GREEN BACKGROUND → DOG

CAT ← GREEN BACKGROUND

Test set

Train and test sets have different conditional probability distributions

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Fixing bias

Train set

Solution?

Fixing bias

Train set

Solution?

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

Fixing bias

Train set

Solution?

THEY WILL **NEVER** BE **EXACTLY EQUAL**

This is why overfitting exists

Fixing bias

Train set

More similarity means **better generalization.** But generalization **to what?**

What is learning about?

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

Train set

GENERALIZATION

Test set

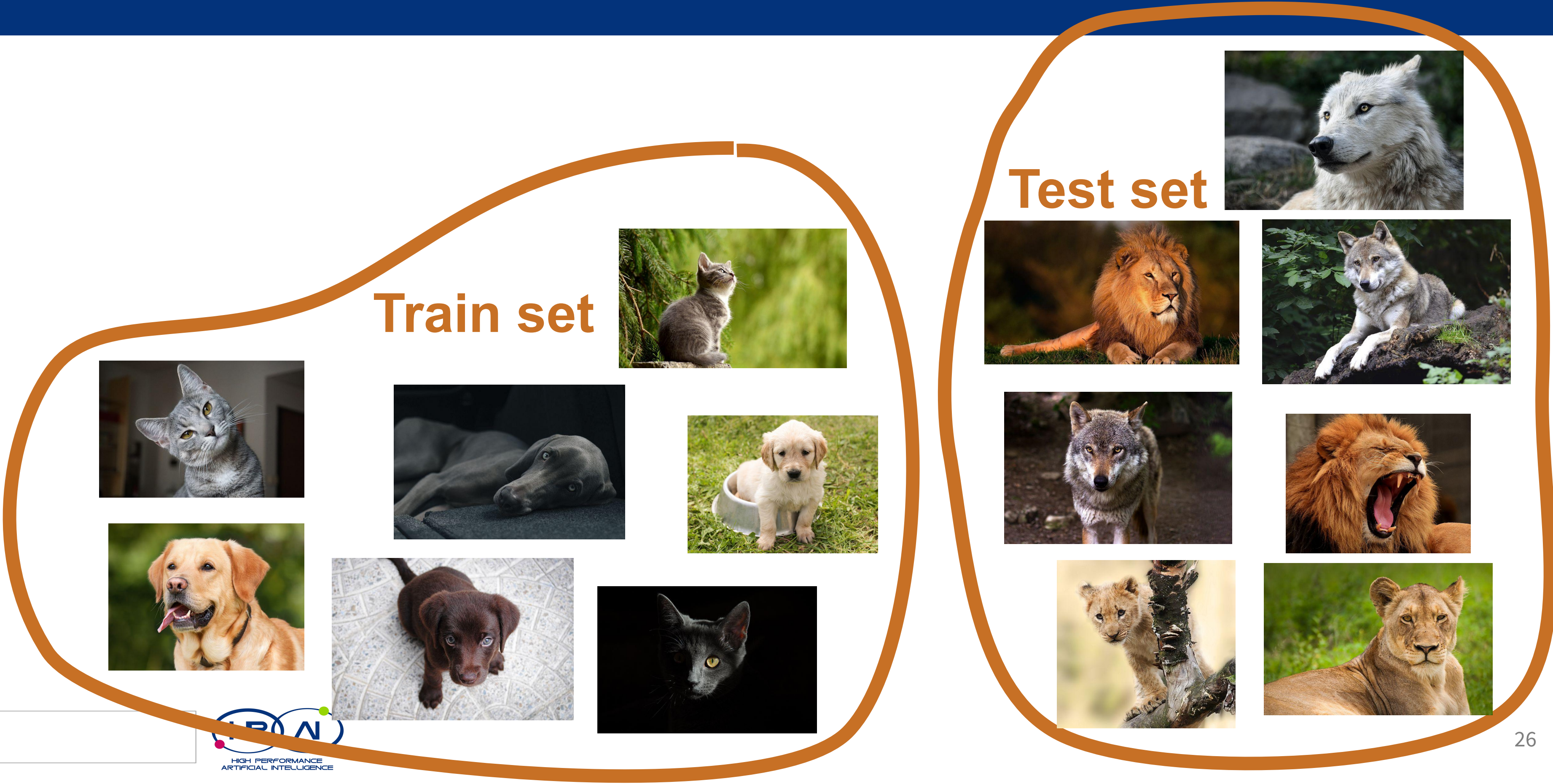
What is learning about?

Is the same source enough?
What do we really want to generalize to?
What is the **real purpose** of the model?
What should we test on?

Train set

GENERALIZATION

A realistic scenario



A realistic scenario

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:

What is the nature of data?

Which is it manifold?

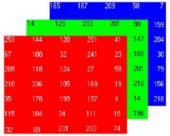
Task:

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:

Task:

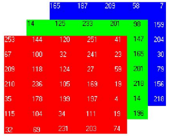
What is the mapping of data?

How is it computed?

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 $P(X), where\ X = \{x_1, \ldots, x_n\} \in \mathcal{X}$



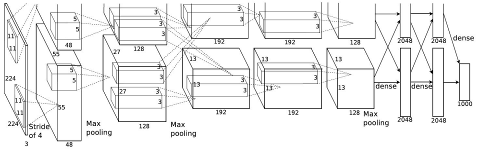

≠

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

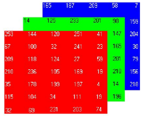
Domain: $\mathcal{D} = \{\mathcal{X}, P(X)\}$

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

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

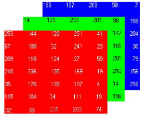
Source

→

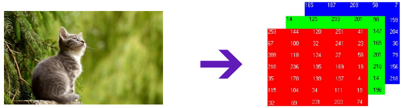
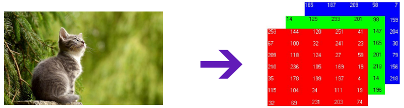
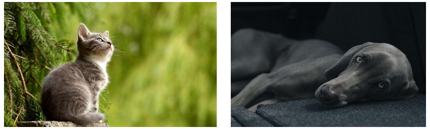


Target

→



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}	{LION, WOLF} {FELINE, CANINE}
• An objective predictive function – **Different (but similar?)**	$f_S(\cdot)$	$f_T(\cdot)$

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What is transfer learning about?

What is transfer learning about?

Target domain

Source domain

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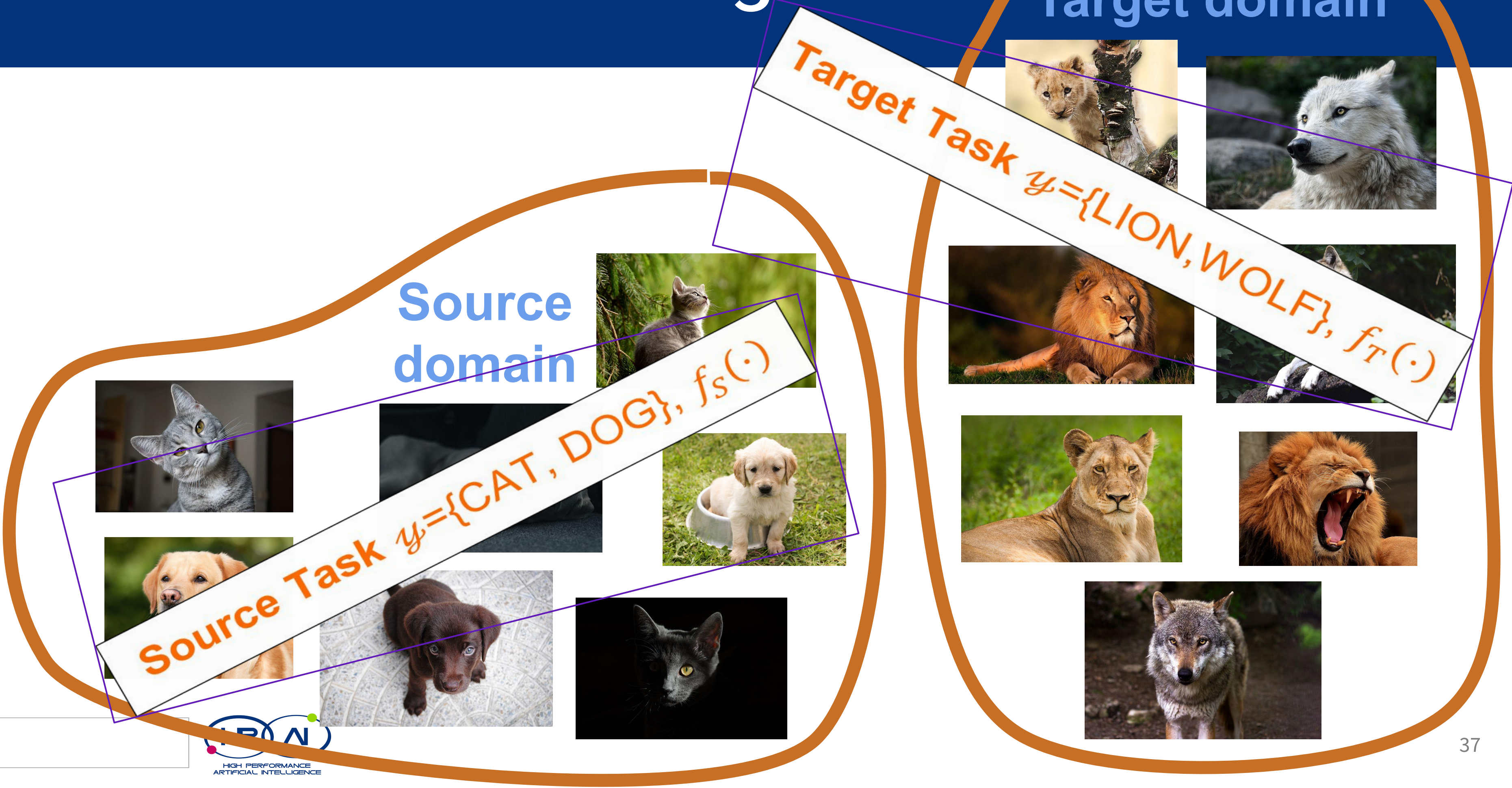
What is transfer learning about?

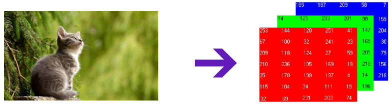


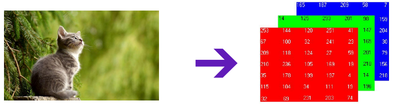
Formalizing transfer learning

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** — Source: **{CAT, DOG}**; Target: **{LION, WOLF}**
  - **The same** — Source: **{FELINE, CANINE}**; Target: **{FELINE, CANINE}**

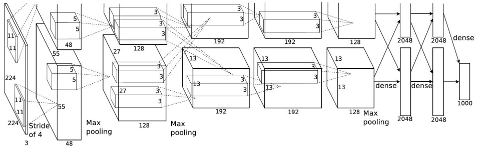
- An objective predictive function — Source: $f_S(\cdot)$; Target: $f_T(\cdot)$
  - **Different (but similar?)**

Formalizing transfer learning

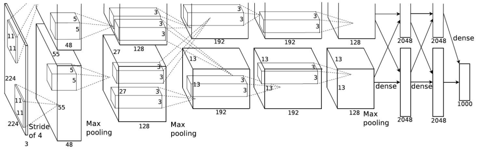
Source $f_S(\cdot)$

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?

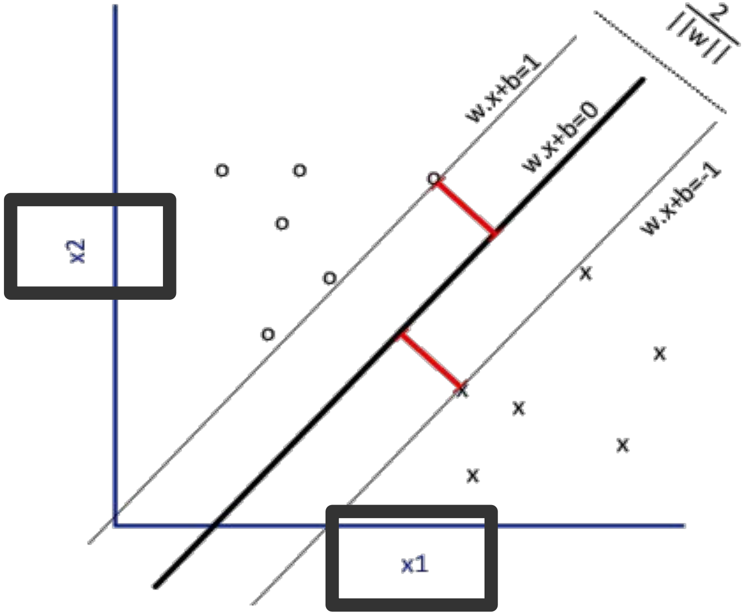
Representation Learning & Classifiers

Learning to describe

A typical classifier

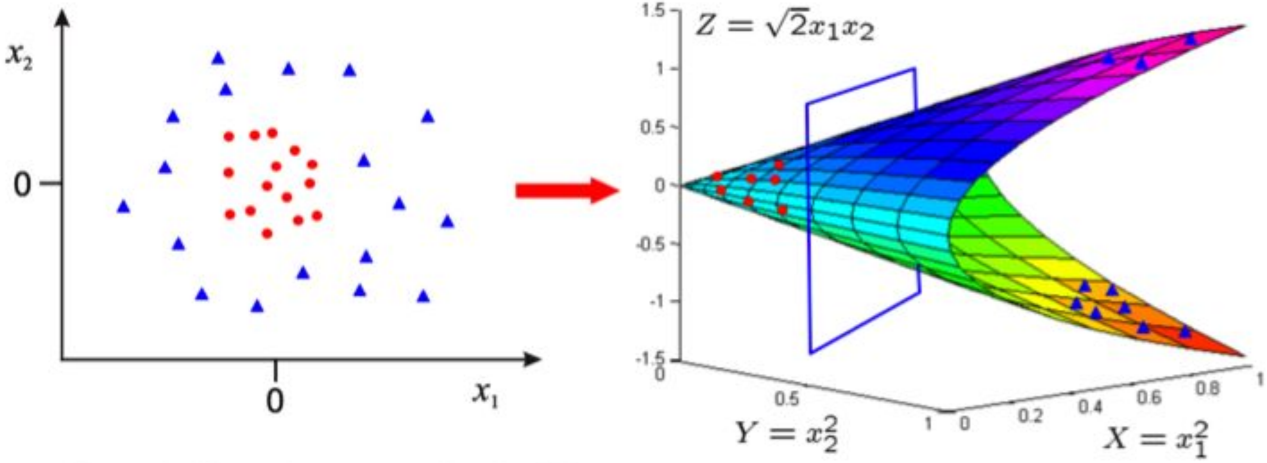
- **Support Vector Machine** (SVM) is just a **classifier** (a very good one).

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

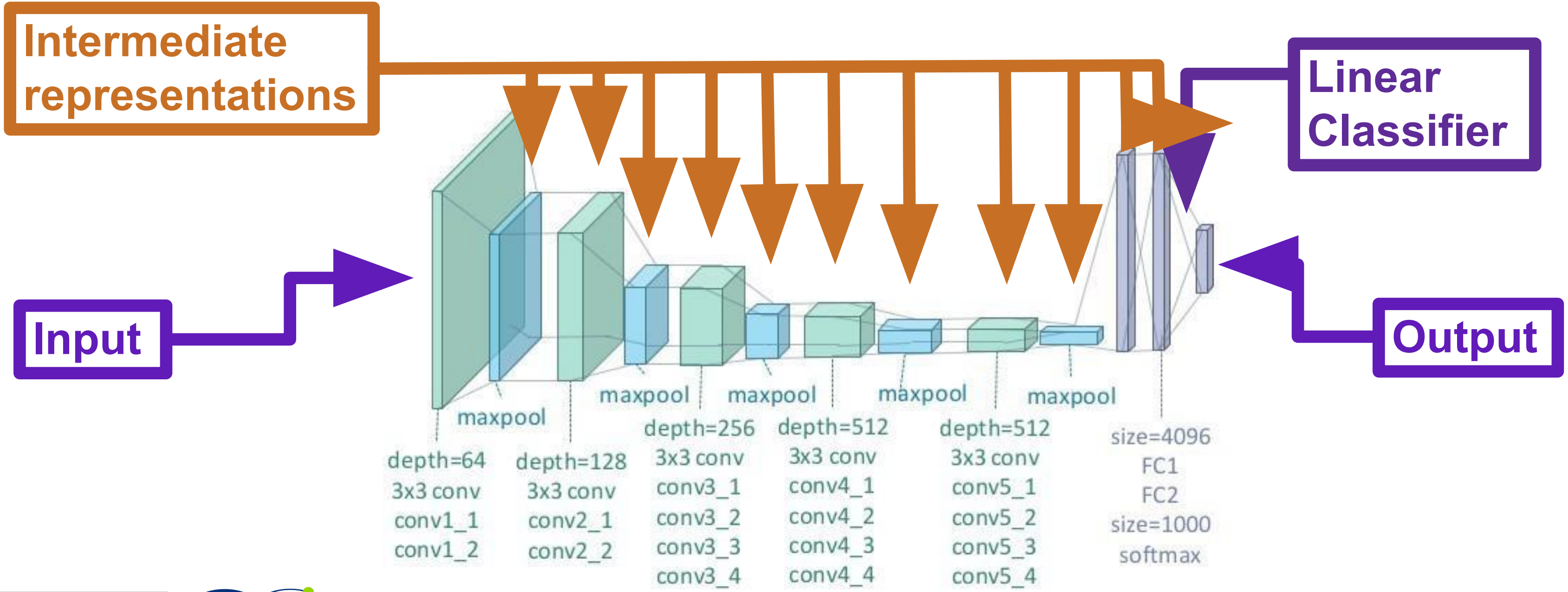


A good classifier

- 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



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Classifiers and Representations

- Classifiers are **Task**-specific
  - We can rarely reuse them for a different task, as they are bounded to the **label space**

- Representations are **Domain**-specific
  - We can often reuse them for a different Task if we remain in the same **feature space**!

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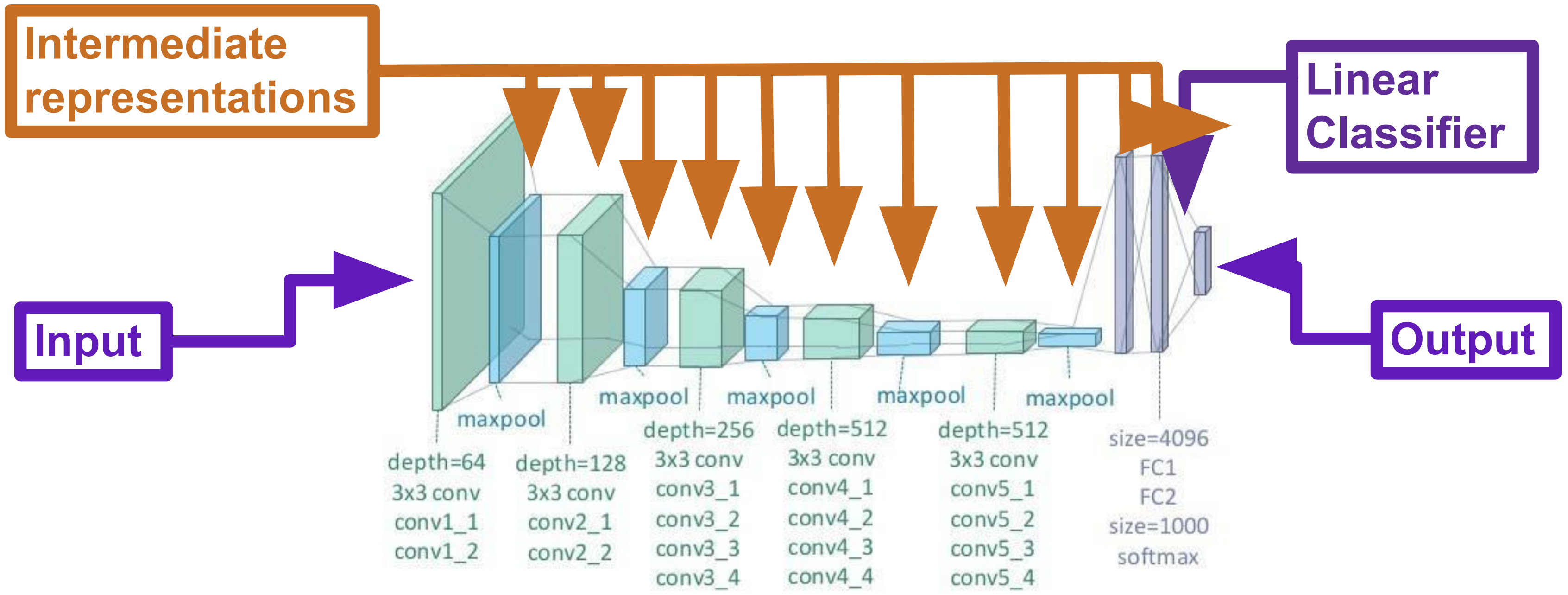
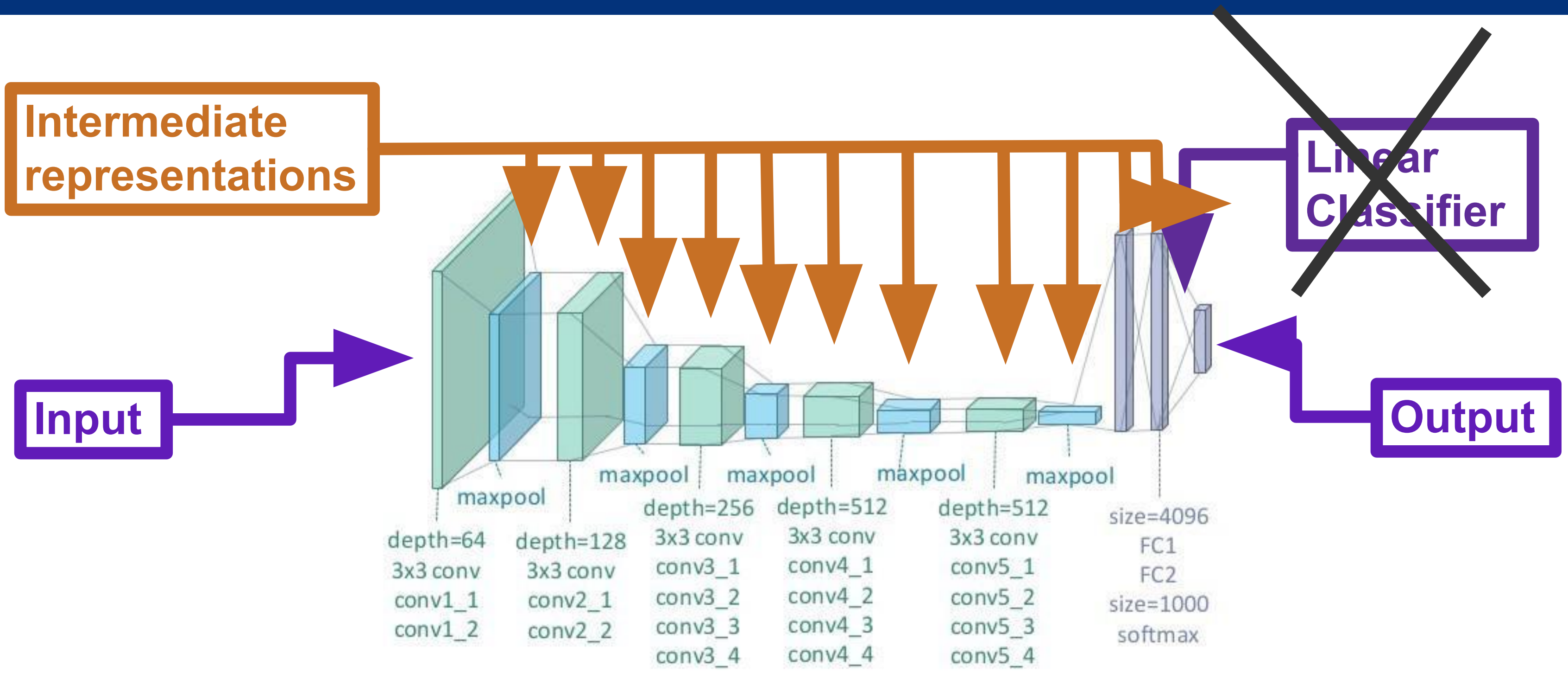
Reusing Deep Representations

Save the Earth - Reuse DNNs

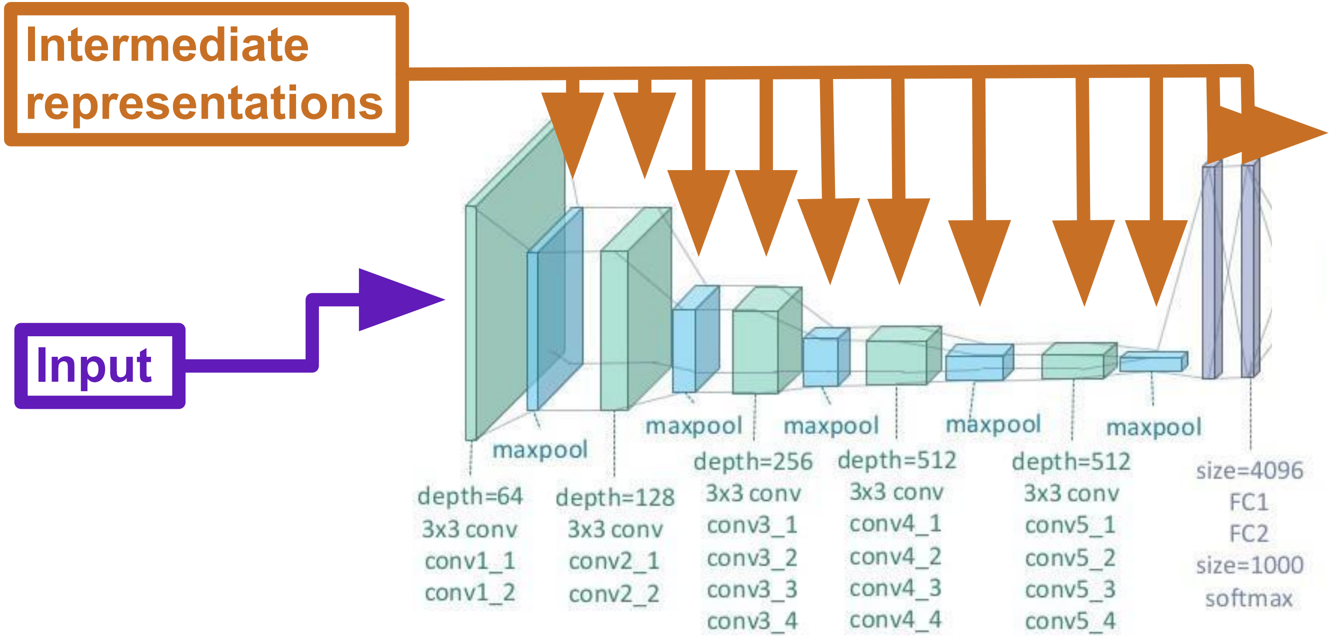
What can be saved?



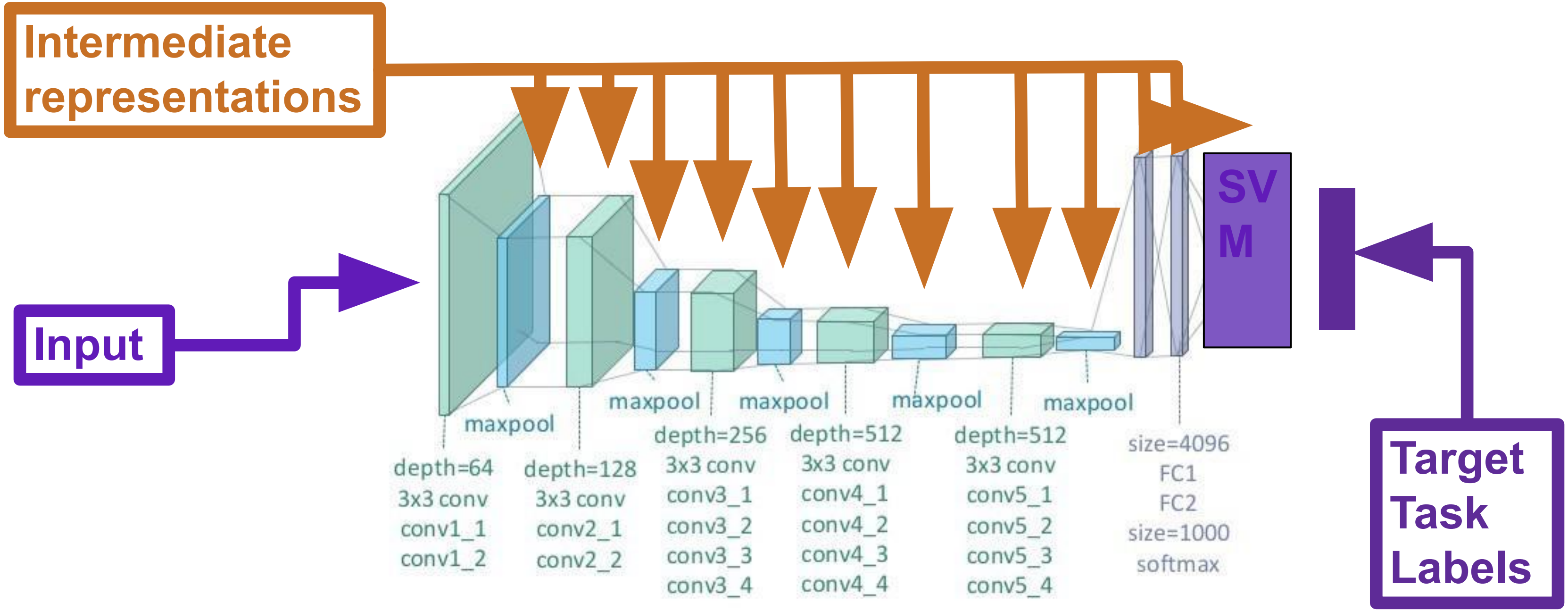
What can be saved?



Feature extraction

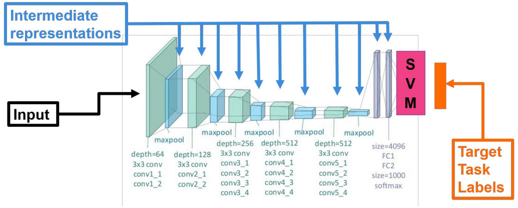


Feature extraction



Reuse All

- DNN last layer features + SVM
  - *Feature extraction*
  - Very similar task and same domain



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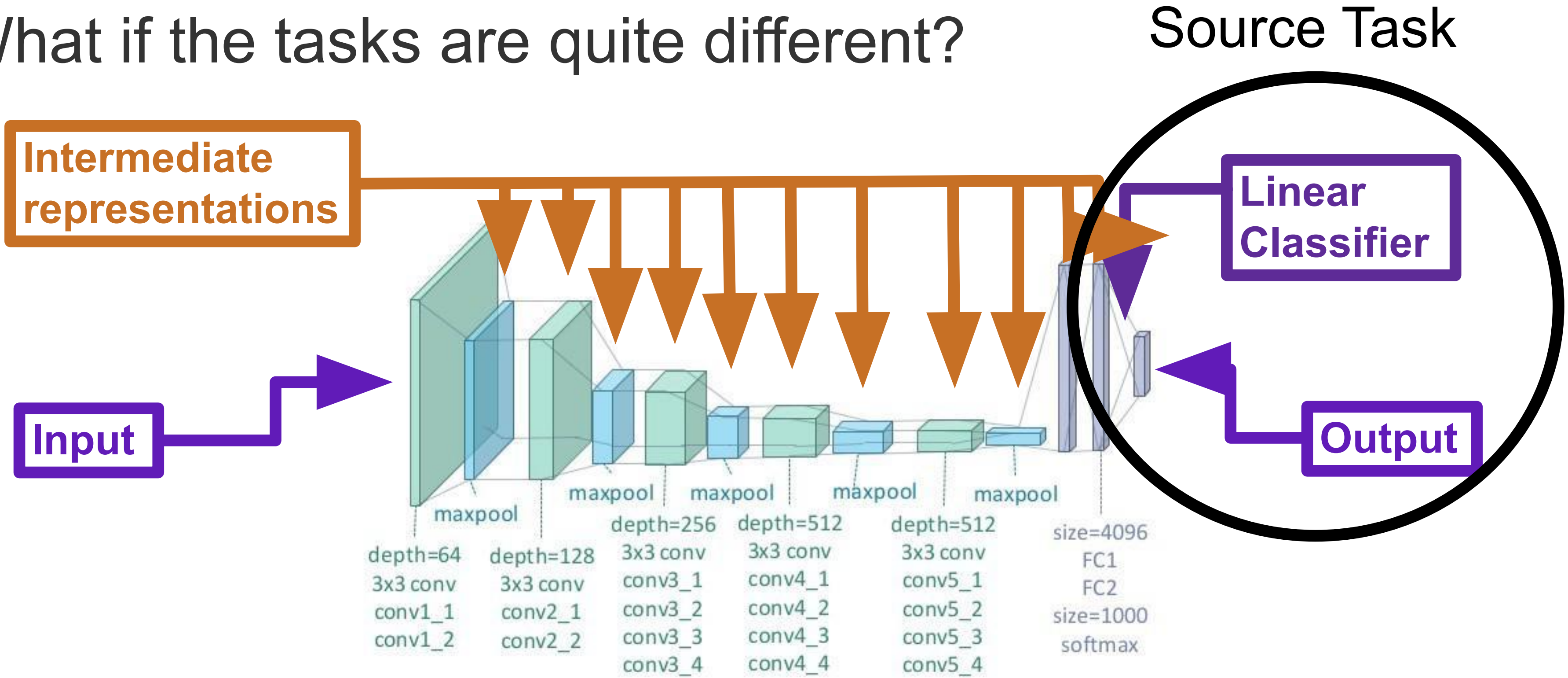
Fine tuning

What if the tasks are quite different?



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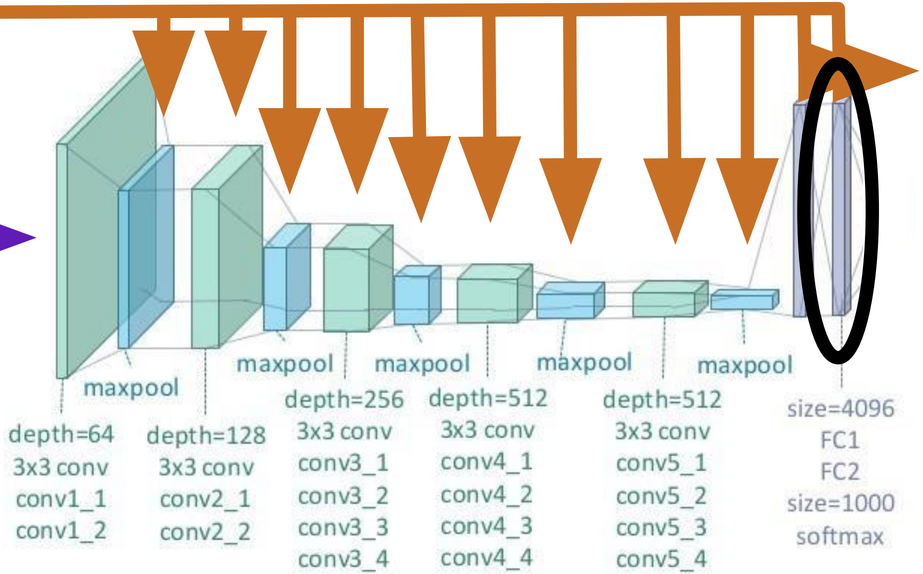
Fine tuning

Intermediate representations

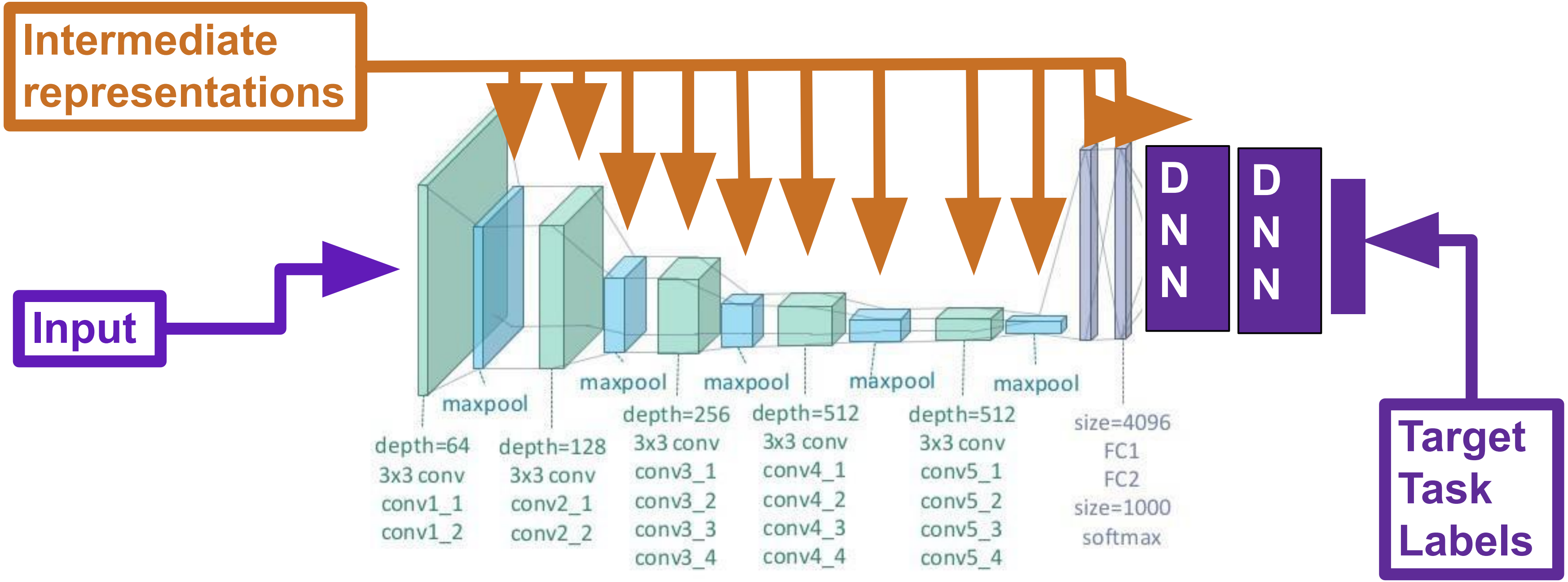
Input



Features learned for the **Source Task**

Can we make them better?

Fine tuning



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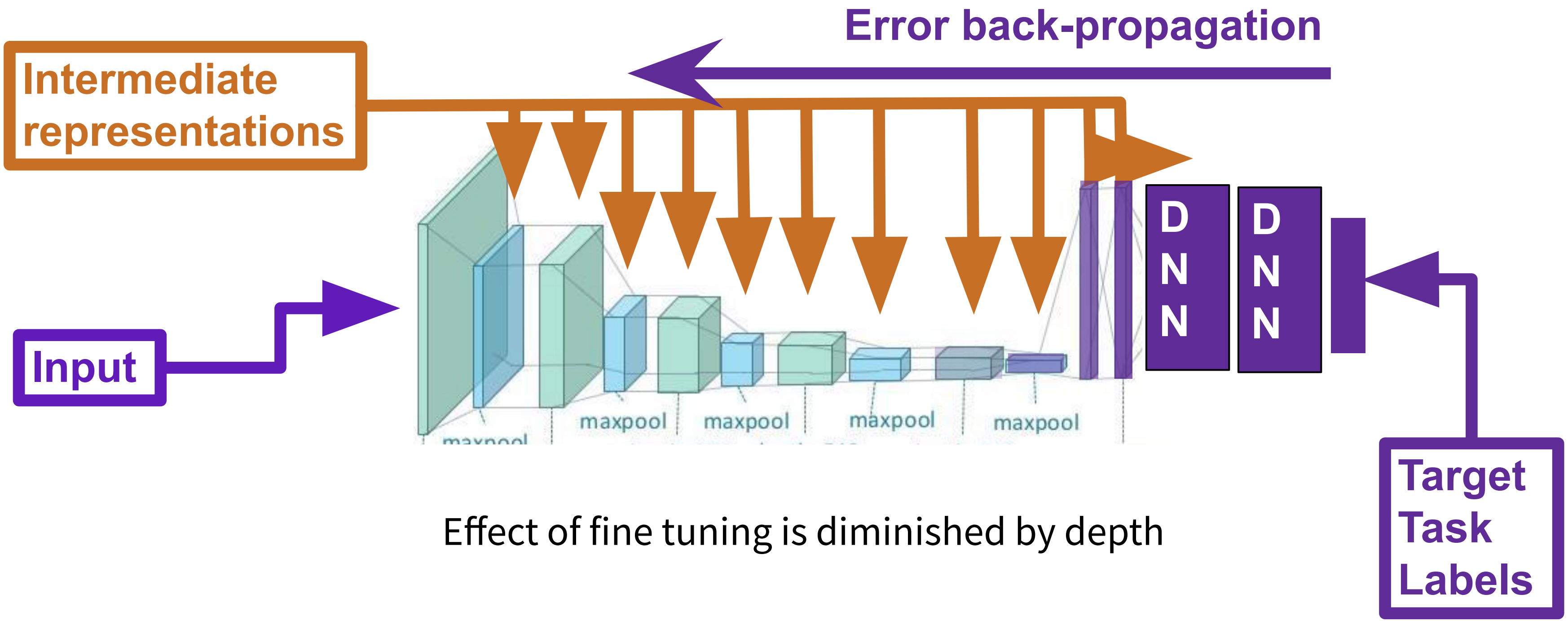
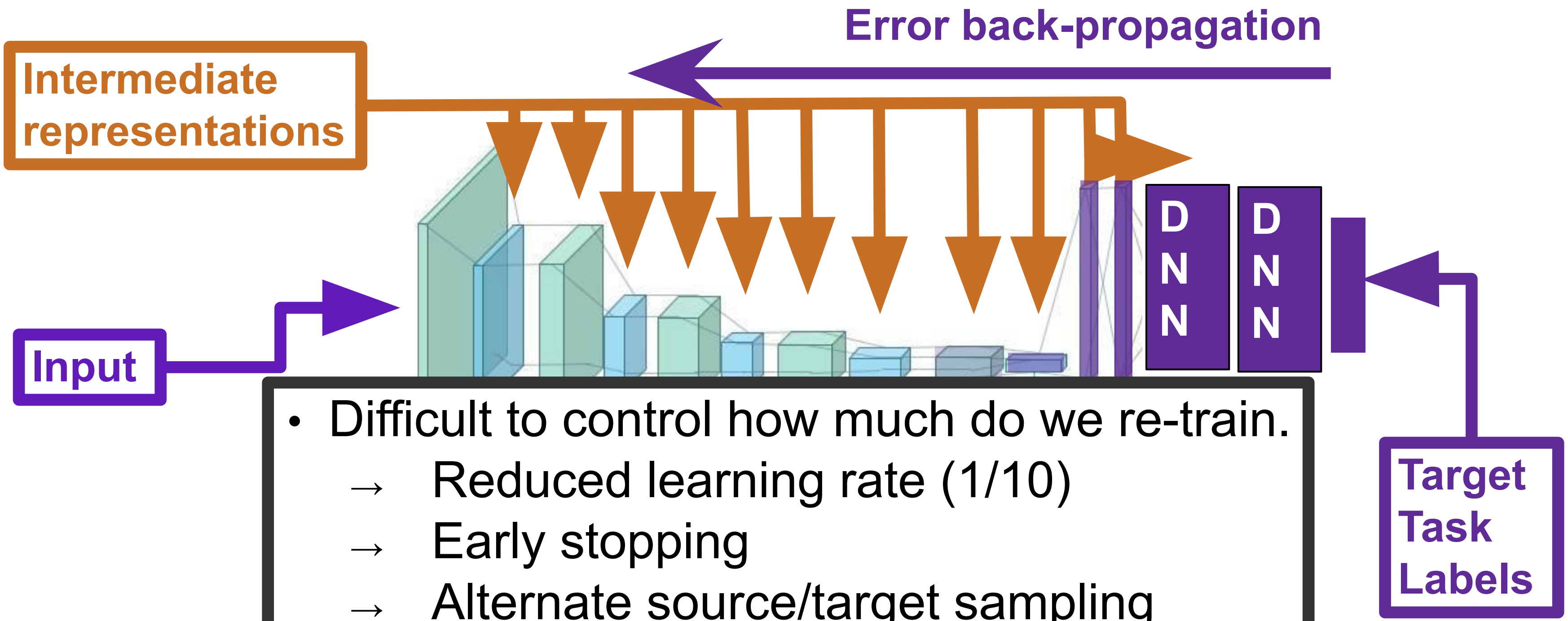
Fine tuning



Effect of fine tuning is diminished by depth

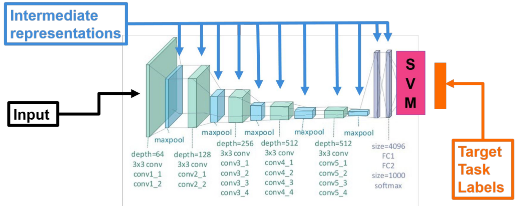
Fine tuning

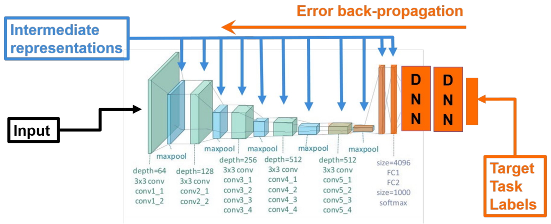


- Difficult to control how much do we re-train.
  - → Reduced learning rate (1/10)
  - → Early stopping
  - → Alternate source/target sampling

Retrain

❖ DNN last layer features + SVM
  ➢ Feature extraction
  ➢ Very similar task and same domain





❖ Train one or several NN layers + pre-trained layers
  ➢ Fine tuning
  ➢ Sort of similar task and same domain
  ➢ Data volume

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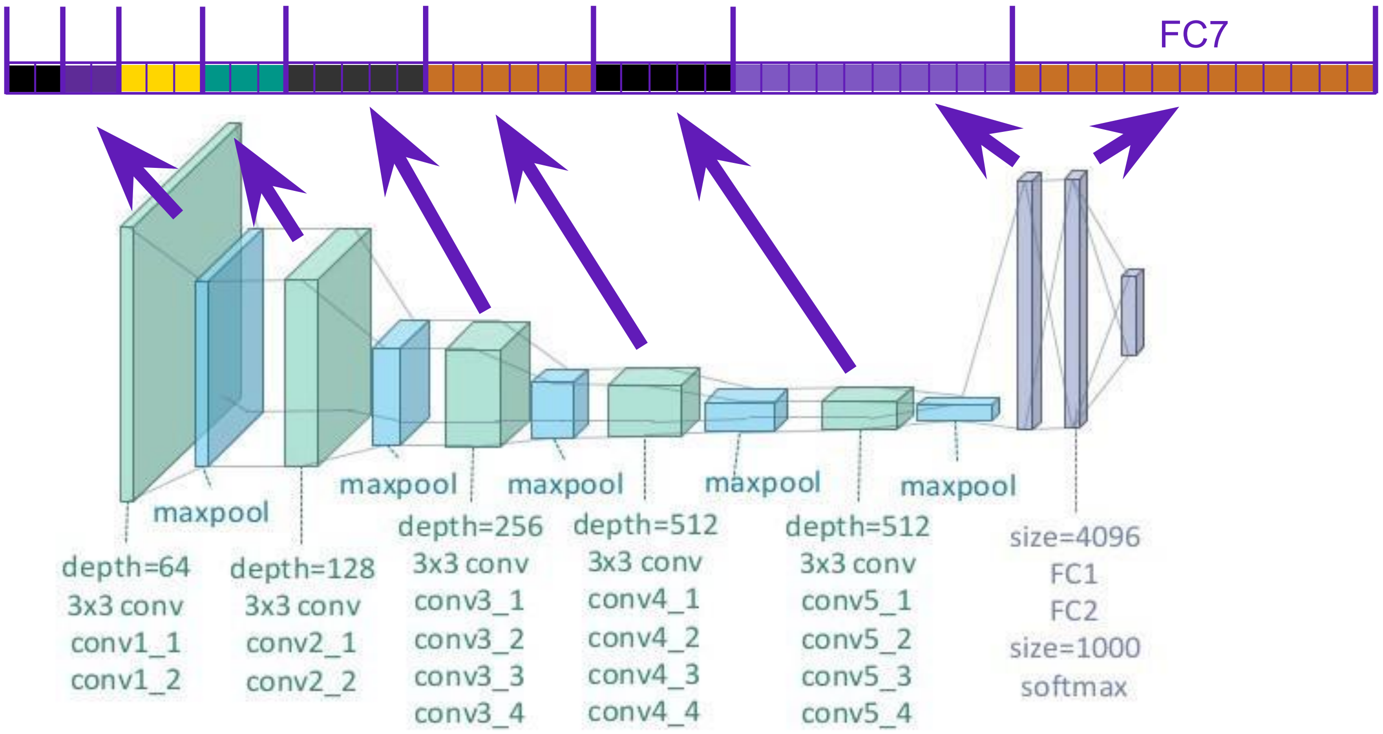
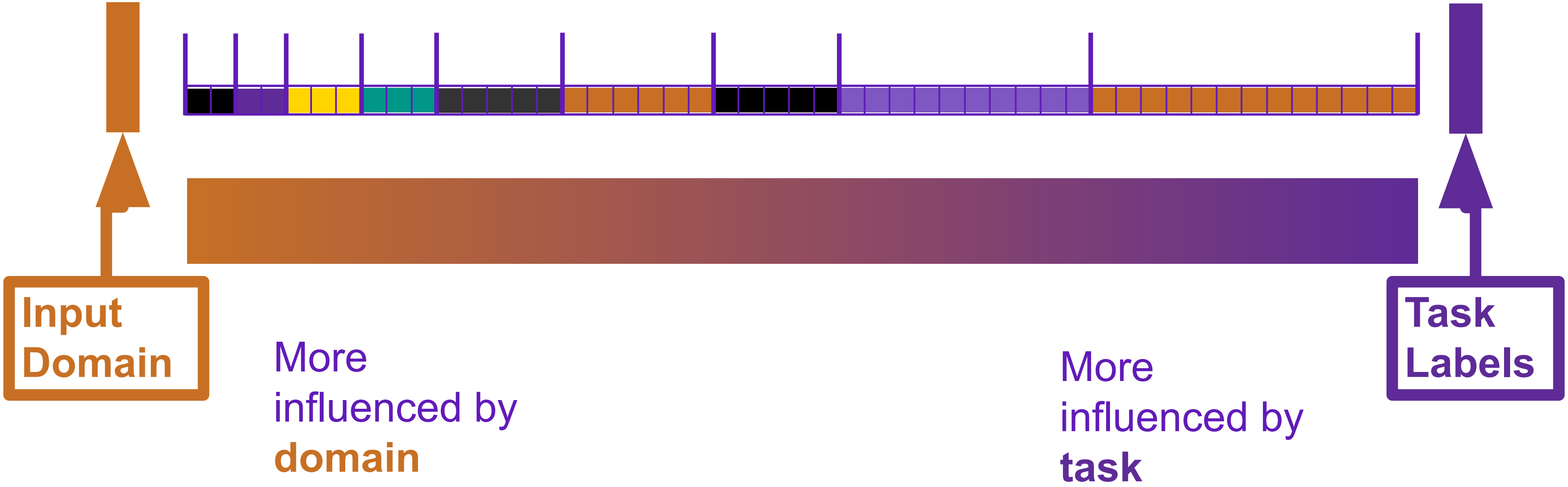
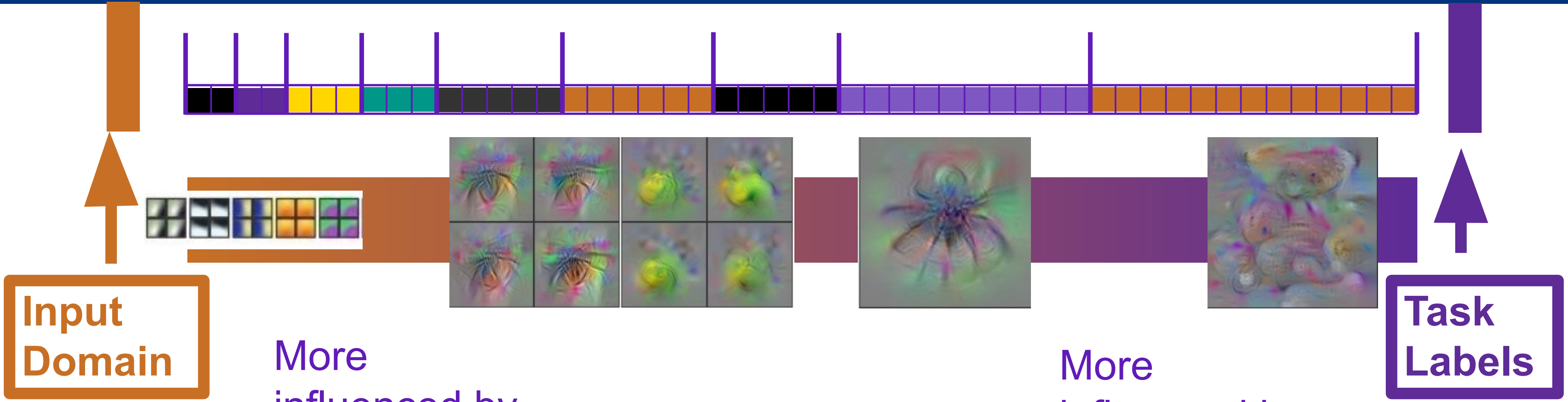
Knowledge inside DNN



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

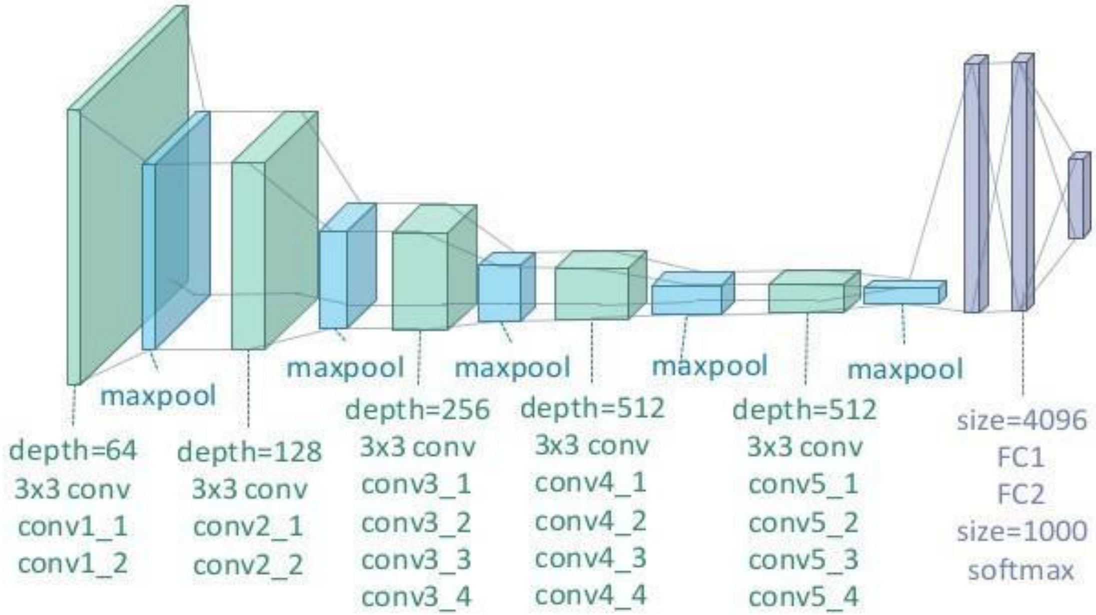
To improve, to remember, to forget

The choices in fine tuning

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

The order of fine tuning

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



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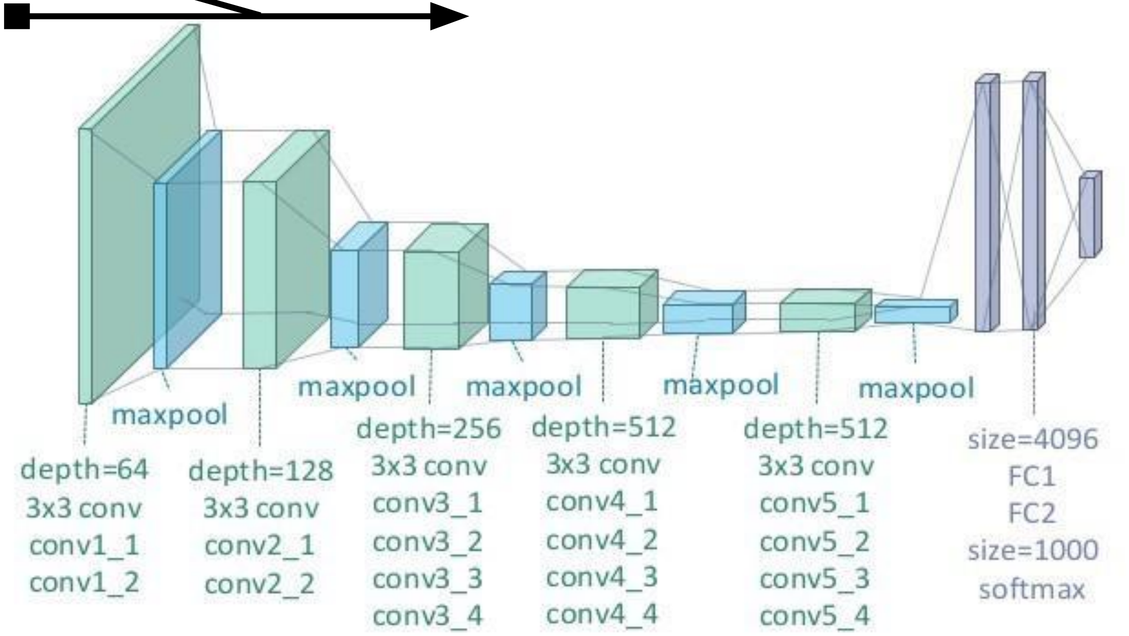
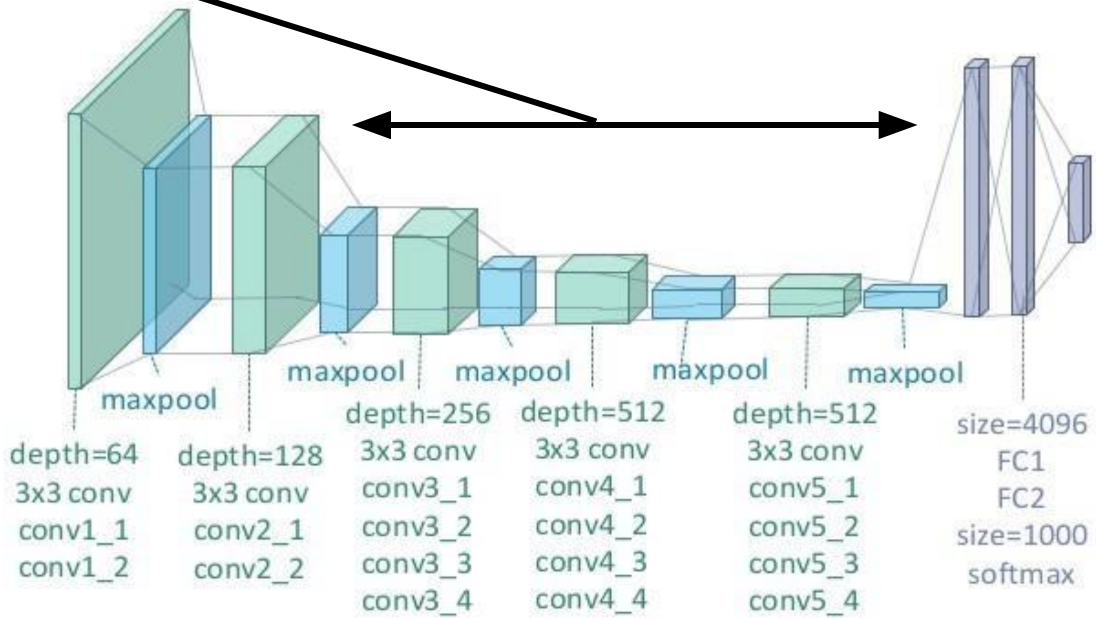
The order of fine tuning

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



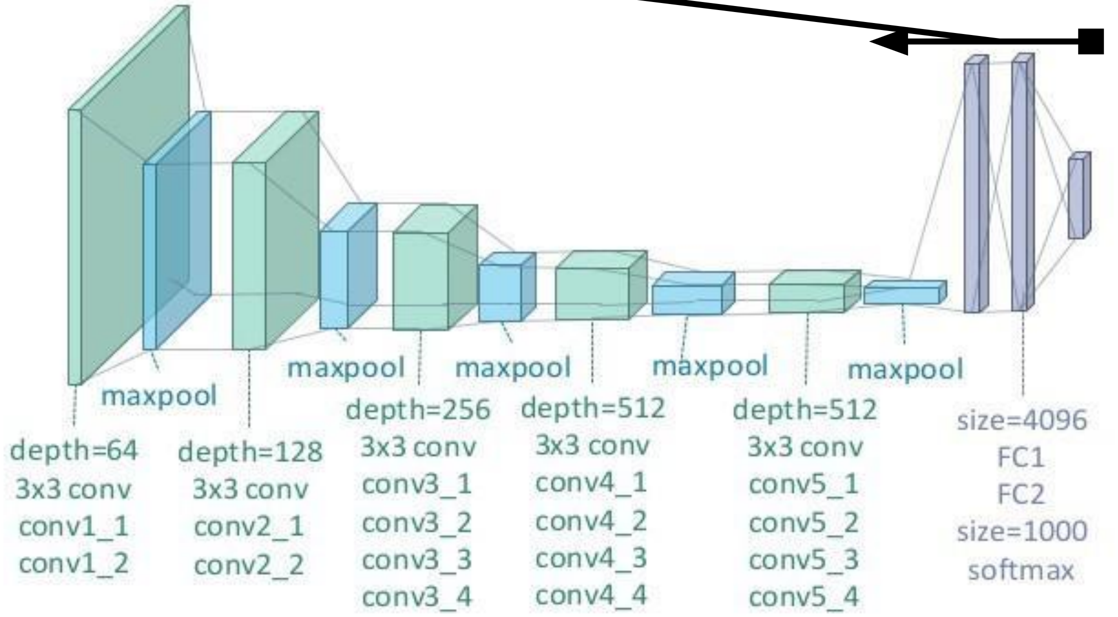
The order of fine tuning

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
- Starting Model
  - Capacity
  - Accuracy

Factors deep representations quality

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If you have all of this, feature extraction plus a classifier will get you *close* to state-of-the-art in 10 minutes of CPU

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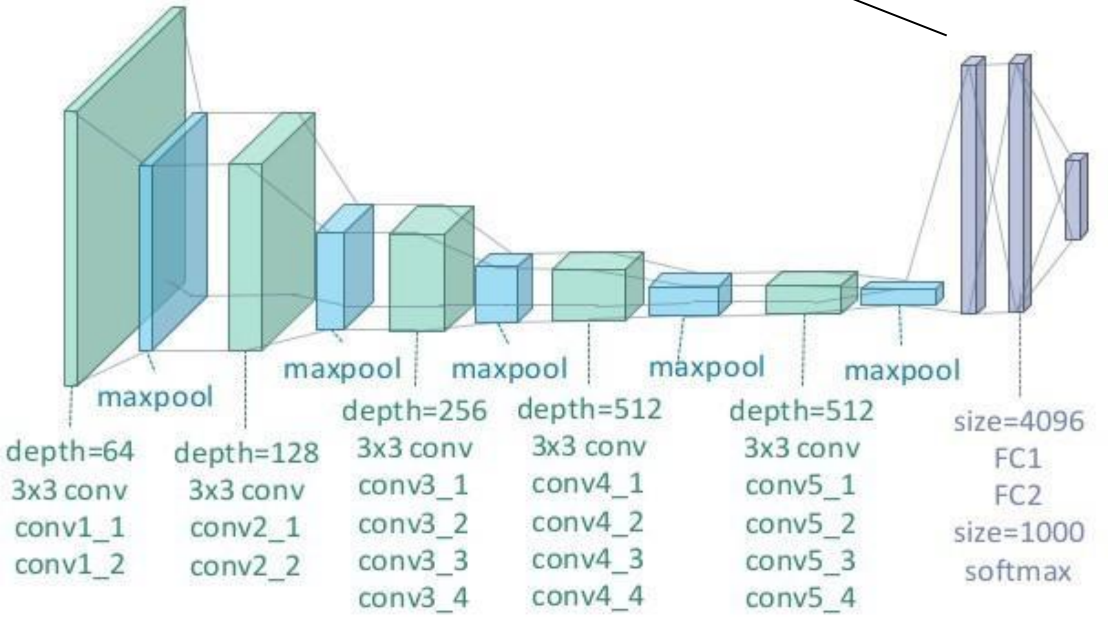
Which layers to use?

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



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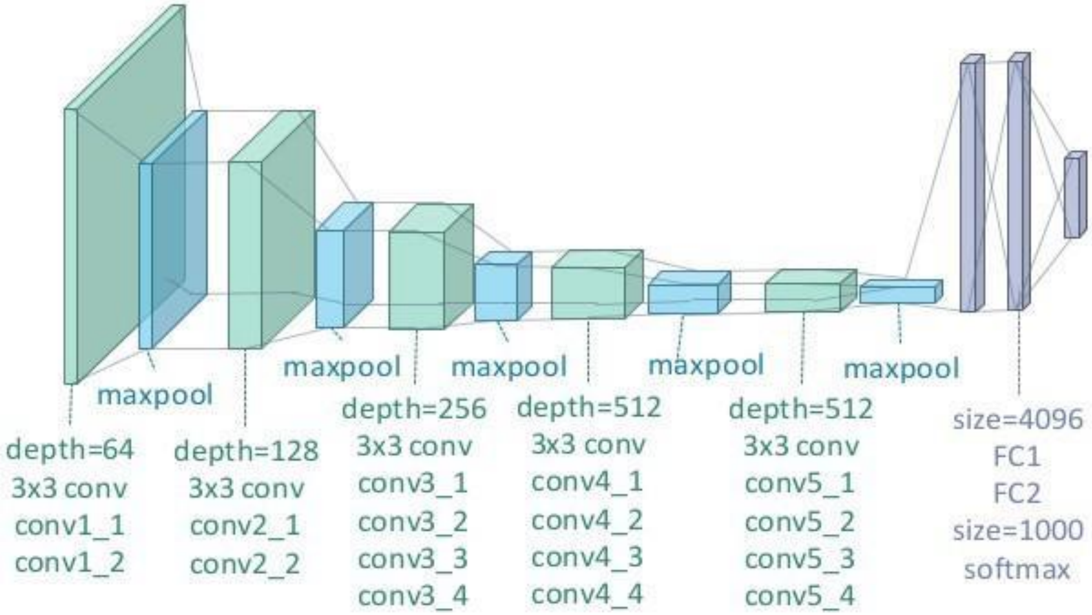
Which layers to use?

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

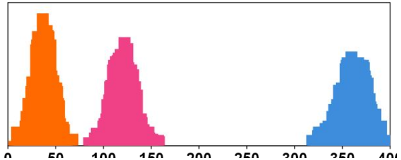


HIGH PERFORMANCE ARTIFICIAL INTELLIGENCE

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!)

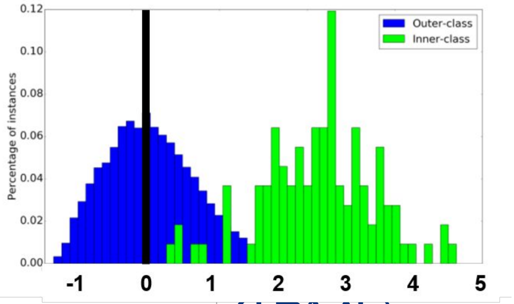
VGG16	*Convs*	*FCs*
# Layers:	14	2
Activations:	33%	66%



Advanced feature normalization

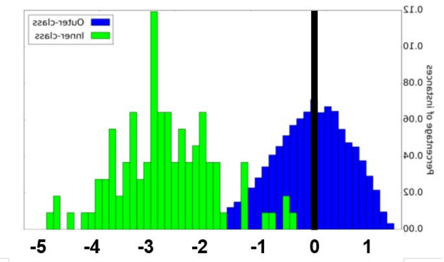
- Normalizing features considering the target
    - Feature standardization (vertically instead of horizontally)
- For each feature..
    - Compute mean and std dev. on *target* training set
    - Normalize feature-wise to zero mean, one std dev.
    - Features are adapted to *target domain*

Best for multi-layer feature extraction



fc7 n1779

Cloister



fc7 n1946

Gadwall

Brown Pelican

White Pelican

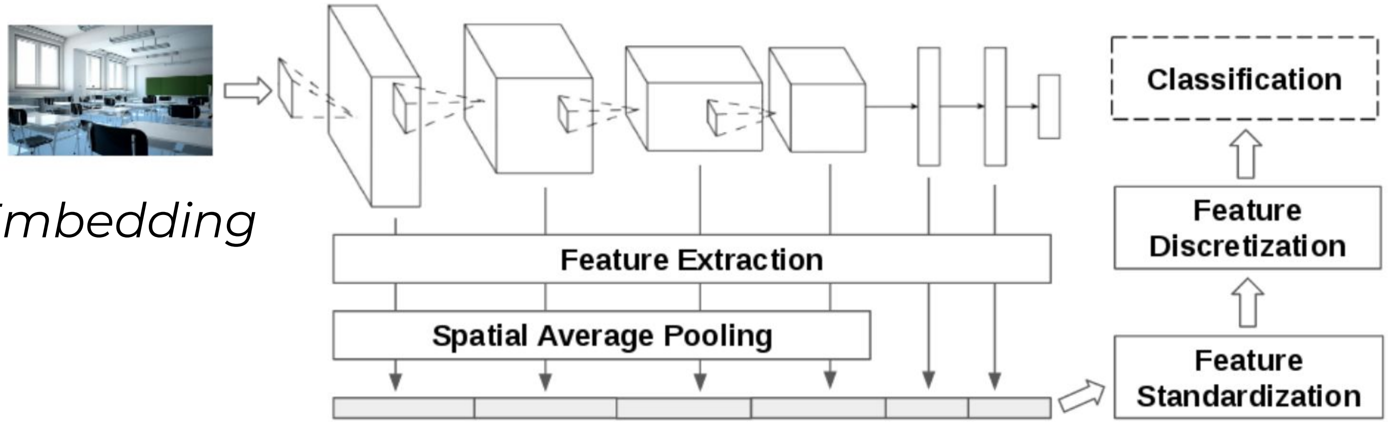
Heermann Gull

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)



HIGH PERFORMANCE ARTIFICIAL INTELLIGENCE

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

- High similarity source - target

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

+7.9

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

HIGH PERFORMANCE ARTIFICIAL INTELLIGENCE

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

HIGH PERFORMANCE ARTIFICIAL INTELLIGENCE

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

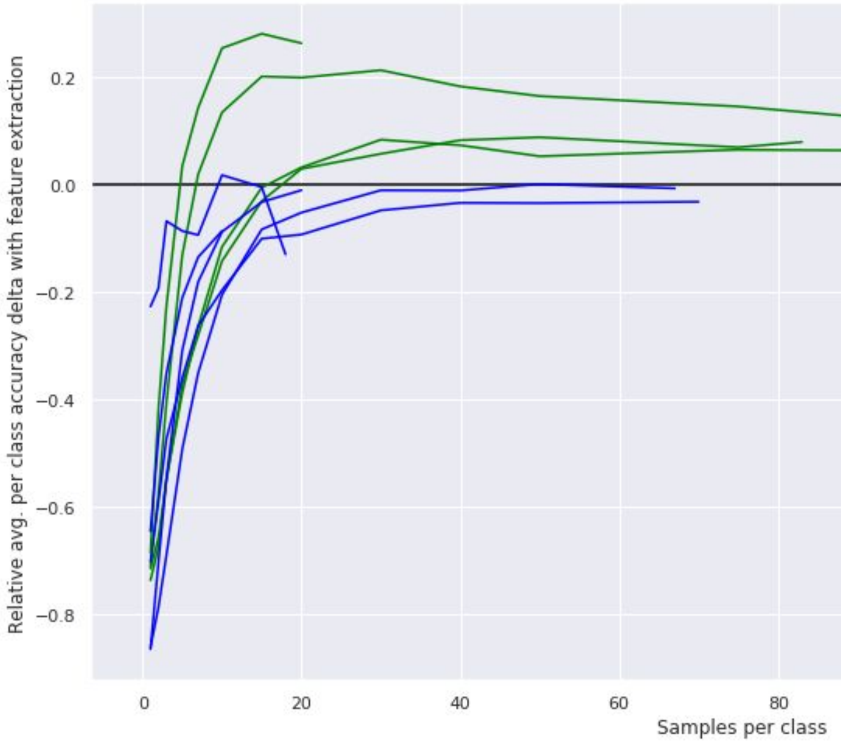
Key takeaways

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

SPOILER!

- Is there a pre-trained model in a **very similar** domain?
    - Yes: Do FT. With 5-10 samples is already bettern than FE.
    - No. Do FE. Unless you have +100 samples/class and/or perform exhaustive hyperparameter tuning.

- What about human cost, time and environmental footprint?



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Dario Garcia-Gasulla (BSC)

dario.garcia@bsc.es

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