



UNIVERSITAT POLITÈCNICA DE CATALUNYA
BARCELONATECH

School of Professional & Executive Development

POSTGRADUATE COURSE

ARTIFICIAL INTELLIGENCE WITH DEEP LEARNING

WWW.TALENT.UPC.EDU



#DLUPC

Day 4 Lab 4

Transfer Learning



Xavier Giro-i-Nieto

xavier.giro@upc.edu

Associate Professor

Universitat Politècnica de Catalunya
Technical University of Catalonia



Daniel Fojo

dani.fojo@gmail.com

Research Engineer

Disney Research



The Concept

Acknowledgements



Kevin McGuinness

kevin.mcguinness@dcu.ie

Research Fellow

Insight Centre for Data Analytics
Dublin City University



Ramon Morros

ramon.morros@upc.edu

Associate Professor

ETSETB TelecomBCN
Universitat Politècnica de Catalunya

Videlectures



DEEP LEARNING FOR COMPUTER VISION
Summer Session UPC TelecomBCN, 8-9 June 2016

Day 2 Lecture 5

Transfer learning and domain adaptation

Instructors: [List of 6 instructors]

Organizers: [Logos of UPC, TelecomBCN, and others]

UPC UNIVERSITAT POLITÈCNICA DE CATALUNYA
BARCELONATECH
Departament de Teoria del Senyal i Comunicacions

[Kevin McGuinness \(UPC DLCV 2016\)](#)



DEEP LEARNING FOR ARTIFICIAL INTELLIGENCE
Master Course UPC ETSETB TelecomBCN, Barcelona, Autumn 2018

Day 5 Lecture 2

Transfer learning and domain adaptation

Instructors: [List of 10 instructors]

Organizers: [Logos of UPC, ETSETB, and others]

Supporters: [Logos of Google Cloud and GitHub Education]

+ Info: <http://bit.ly/dlai2018>

#DLUPC

Many slides from:



Ramon Morros
Associate Professor
TelecomBCN, UPC, and ETSETB
Technical University of Catalonia



Kevin McGuinness
Senior Research Engineer
NVIDIA, Dublin
Research Center for Deep Learning
NVIDIA, Dublin



Eric Arazo
PhD Candidate
TelecomBCN, UPC, and ETSETB
Technical University of Catalonia

[course site]

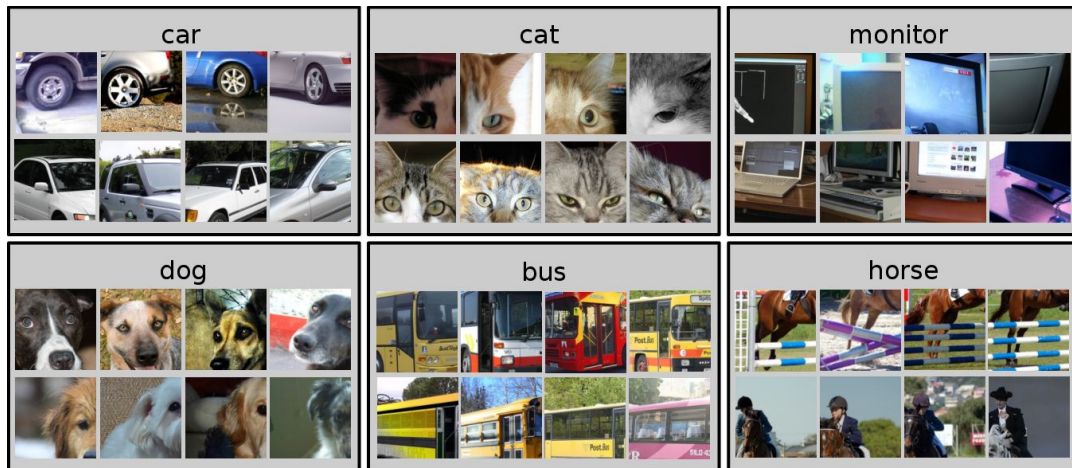
[Ramon Morros \(UPC DLAI 2018\)](#)

Transfer learning: the motivation

- In many cases, not enough training data is available to estimate the large amount of parameters required by a deep neural network.

Example: PASCAL VOC 2007

- Standard classification benchmark, 20 classes, ~10K images, 50% train, 50% test
- Deep networks can have many parameters (e.g. 60M in Alexnet)
- Direct training (from scratch) using only 5K training images can be problematic. Model overfits.
- How can we use deep networks in this setting?

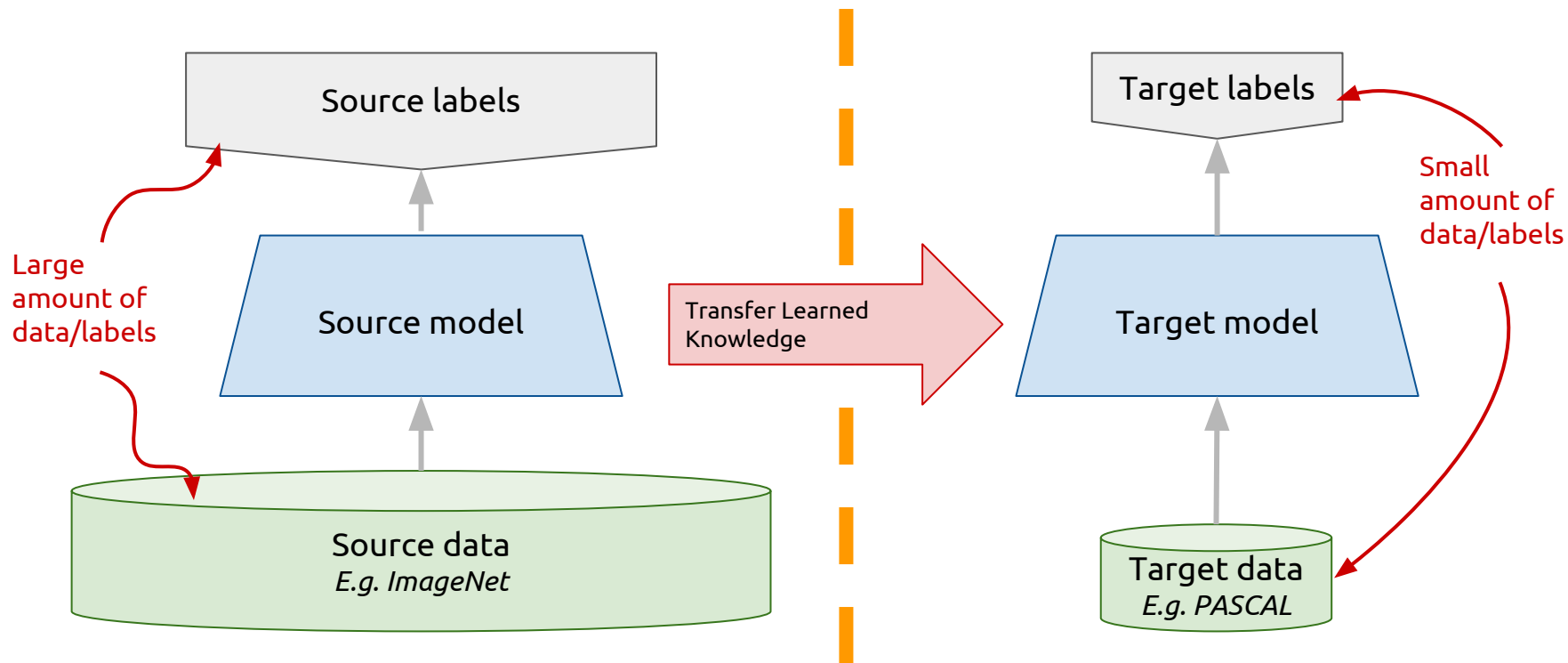


Transfer learning: the solution

Instead of training a deep network from scratch for your task:

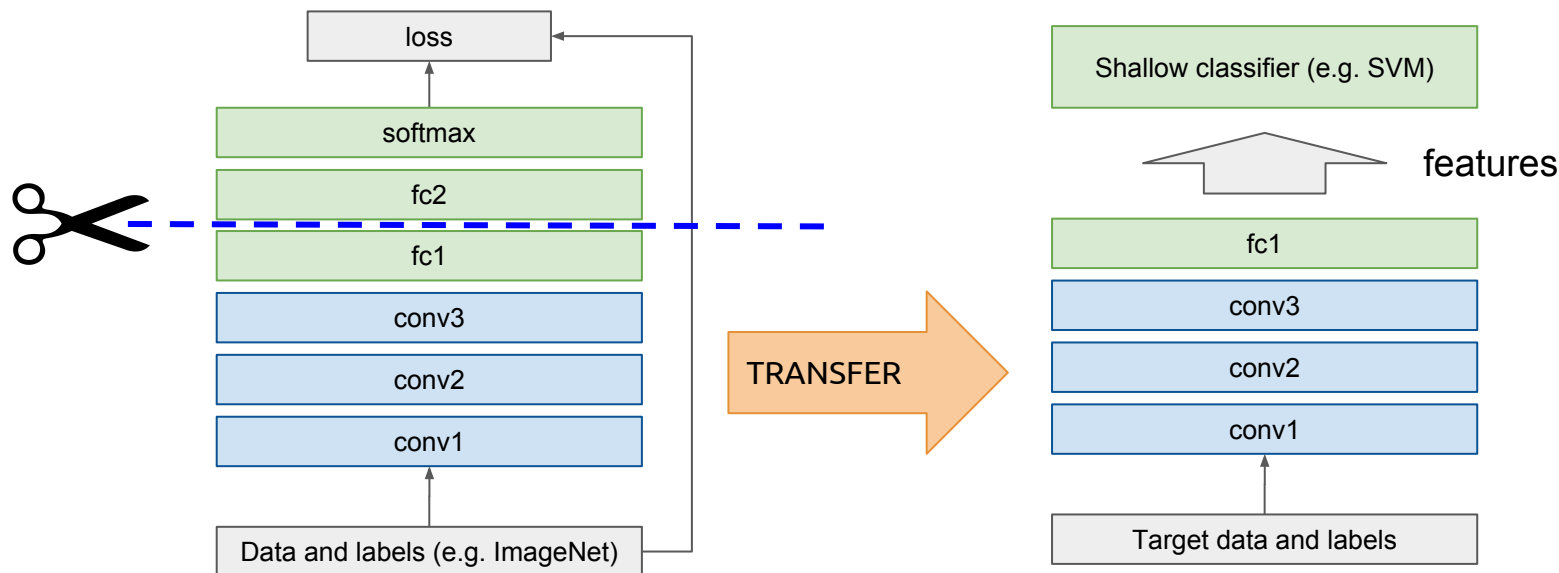
- Take a network trained on a different domain for a different **source task**
- Adapt it for your domain and your **target task**

Transfer learning: idea



“Off-the-shelf”

Idea: use outputs of one or more layers of a network trained on a different task as generic feature detectors. Train a new shallow model on these features.



Off-the-shelf features

Works surprisingly well in practice!

Surpassed or on par with state-of-the-art in several tasks in 2014

Image classification:

- PASCAL VOC 2007
- Oxford flowers
- CUB Bird dataset
- MIT indoors

Image retrieval:

- Paris 6k
- Holidays
- UKBench

Method	mean Accuracy
HSV [27]	43.0
SIFT internal [27]	55.1
SIFT boundary [27]	32.0
HOG [27]	49.6
HSV+SIFTi+SIFTb+HOG(MKL) [27]	72.8
BOW(4000) [14]	65.5
SPM(4000) [14]	67.4
FLH(100) [14]	72.7
BiCos seg [7]	79.4
Dense HOG+Coding+Pooling[2] w/o seg	76.7
Seg+Dense HOG+Coding+Pooling[2]	80.7
CNN-SVM w/o seg	74.7
CNNaug-SVM w/o seg	86.8

Oxford 102 flowers dataset

Can we do better than off the shelf features?

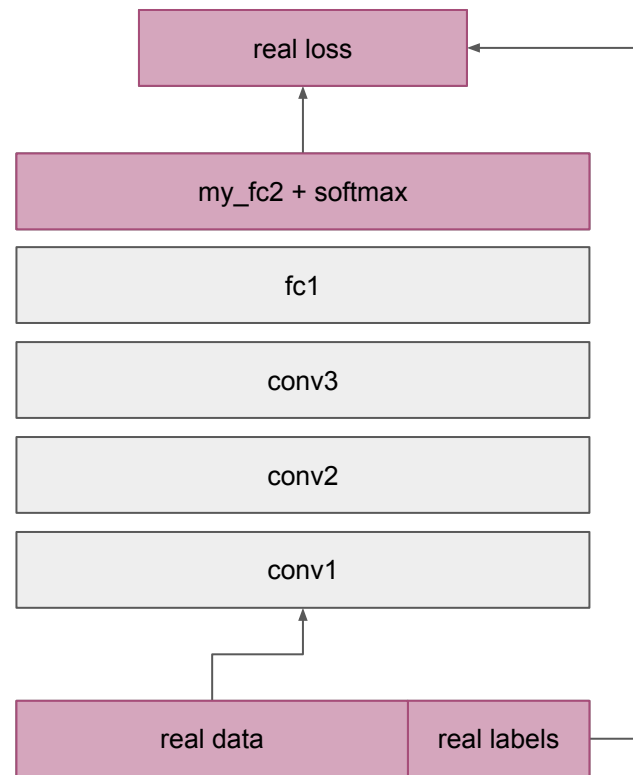
Fine-tuning: supervised task adaptation

Train deep net on “nearby” task for which it is easy to get labels using standard backprop

- E.g. ImageNet classification
- Pseudo classes from augmented data
- Slow feature learning, ego-motion

Cut off top layer(s) of network and replace with supervised objective for target domain

Fine-tune network using backprop with labels for target domain until validation loss starts to increase



Freeze or fine-tune?

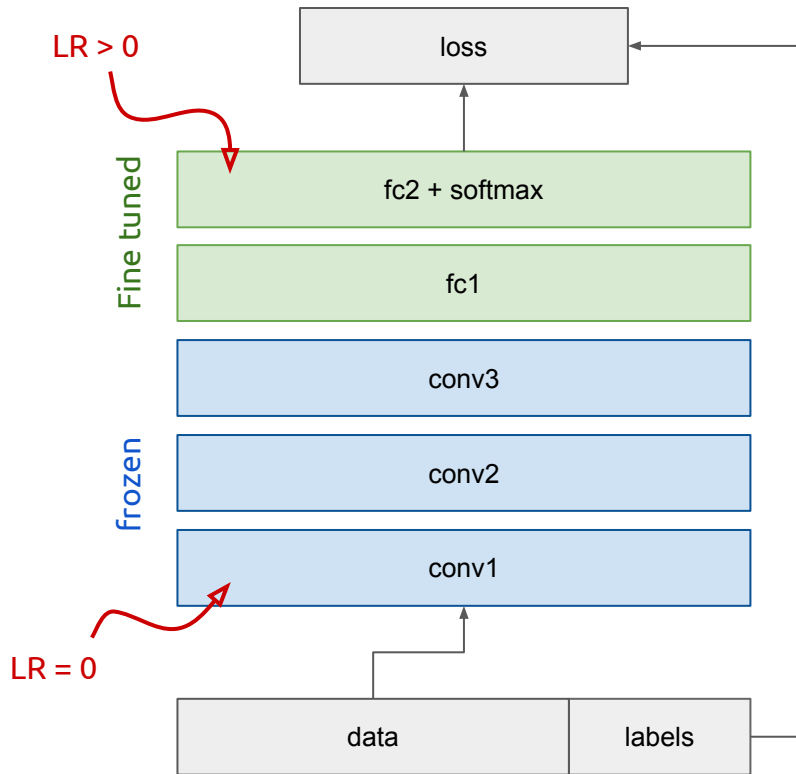
Bottom n layers can be frozen or fine tuned.

- **Frozen:** not updated during backprop
- **Fine-tuned:** updated during backprop

Which to do depends on target task:

- **Freeze:** target task labels are scarce, and we want to avoid overfitting
- **Fine-tune:** target task labels are more plentiful

In general, we can set learning rates to be different for each layer to find a tradeoff between freezing and fine tuning



How are they related?

What do unsupervised learning, semi-supervised learning, and transfer learning have in common?

We often do not have complete access to the y -value that we care about.

Use a **surrogate objective** when y -value unavailable:

- Loss you do not care directly about.
- You expect that improving this loss will help with what you do care about.

Transfer learning uses different dataset in which there are lots of y -values to create a surrogate objective.

Unsupervised tries to formulate surrogate objectives without any manual labels.

Summary

- Possible to train very large models on small data by using transfer learning and domain adaptation
- Off the shelf features work very well in various domains and tasks
- Lower layers of network contain very generic features, higher layers more task specific features
- Supervised domain adaptation via fine tuning almost always improves performance
- Possible to do unsupervised domain adaptation by matching feature distributions

Additional resources

- Lluís Castrejon, "[Domain adaptation and zero-shot learning](#)". University of Toronto 2016.
- Hoffman, J., Guadarrama, S., Tzeng, E. S., Hu, R., Donahue, J., Girshick, R., ... & Saenko, K. (2014). [LSDA: Large scale detection through adaptation](#). NIPS 2014. ([Slides by Xavier Giró-i-Nieto](#))
- Yosinski, Jason, Jeff Clune, Yoshua Bengio, and Hod Lipson. "[How transferable are features in deep neural networks?](#)" In Advances in Neural Information Processing Systems, pp. 3320-3328. 2014.
- Shao, Ling, Fan Zhu, and Xuelong Li. "[Transfer learning for visual categorization: A survey](#)." Neural Networks and Learning Systems, IEEE Transactions on 26, no. 5 (2015): 1019-1034.
- Chen, Tianqi, Ian Goodfellow, and Jonathon Shlens. "[Net2Net: Accelerating Learning via Knowledge Transfer](#)." ICLR 2016. [[code](#)] [[Notes by Hugo Larrochelle](#)]
- Gani, Yaroslav, Evgeniya Ustinova, Hana Ajakan, Pascal Germain, Hugo Larochelle, François Laviolette, Mario Marchand, and Victor Lempitsky. "[Domain-Adversarial Training of Neural Networks](#)." arXiv preprint arXiv:1505.07818 (2015).

Data Augmentation



Eva Mohedano

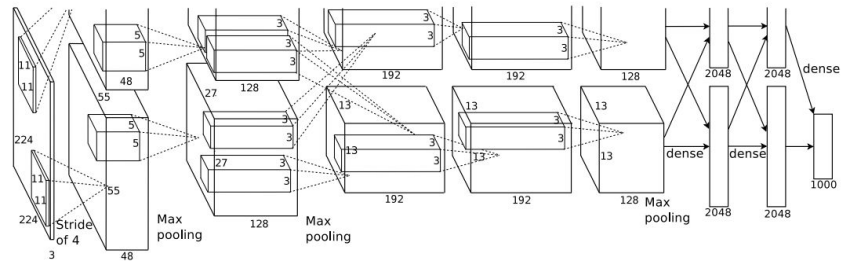
Research Fellow

Insight Centre for Data Analytics
Dublin City University



Ways to reduce overfitting

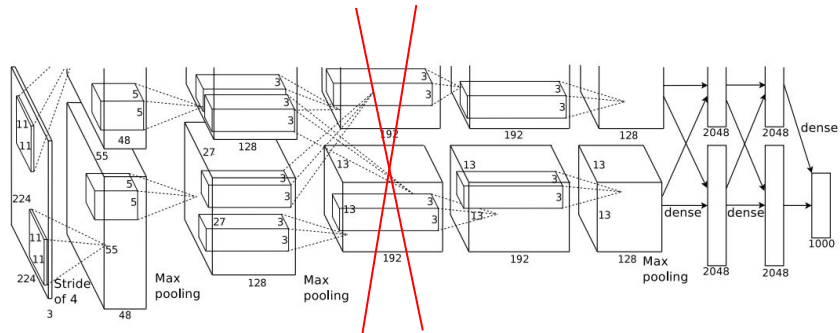
- **Reduce network capacity**
- Dropout
- Data augmentation



Ways to reduce overfitting

- **Reduce network capacity**

- Dropout



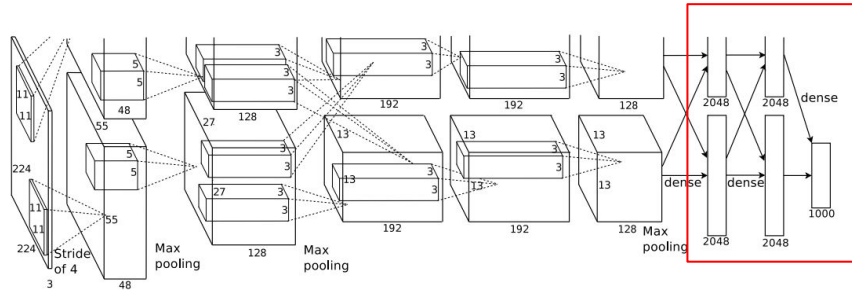
1% of total parameters (884K). Decrease in performance

- Data augmentation

Ways to reduce overfitting

- **Reduce network capacity**

- Dropout



37M, 16M, 4M parameters!! (fc6,fc7,fc8)

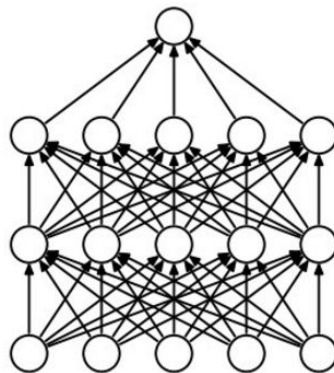
- Data augmentation

Ways to reduce overfitting

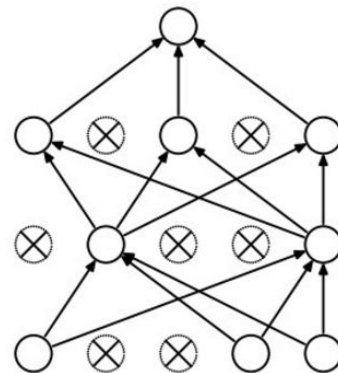
- Reduce network capacity

- **Dropout**

- Data augmentation



(a) Standard Neural Net



(b) After applying dropout.

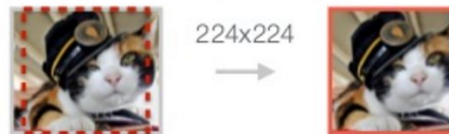
Every forward pass, network slightly different.
Reduce co-adaptation between neurons
More robust features

More iterations for convergence

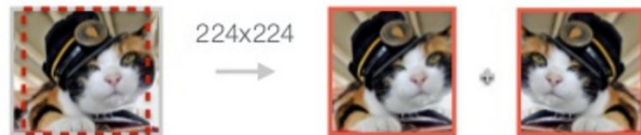
Ways to reduce overfitting

- Reduce network capacity
- Dropout
- **Data augmentation**

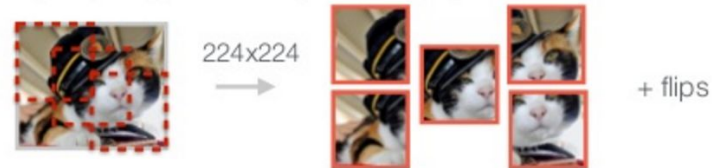
a. No augmentation (= 1 image)



b. Flip augmentation (= 2 images)



c. Crop+Flip augmentation (= 10 images)



Data Augmentation

During training, modify the input image (Krizhevsky A., 2012)

- Random crops on the original image
- Translations
- Horizontal reflections
- Increases size of training x2048
- On-the-fly augmentation

During testing

- Average prediction of image augmented by the four corner patches and the center patch + flipped image. (10 augmentations of the image)

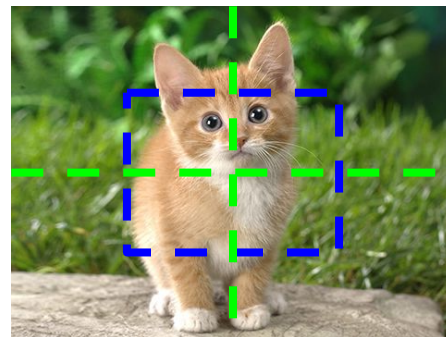
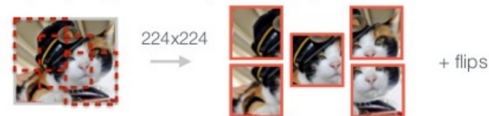
a. No augmentation (= 1 image)



b. Flip augmentation (= 2 images)



c. Crop+Flip augmentation (= 10 images)



The Lab

Acknowledgements



Víctor Campos

victor.campos@bsc.es

PhD Candidate

Barcelona Supercomputing Center



Míriam Bellver

miriam.bellver@bsc.edu

PhD Candidate

Barcelona Supercomputing Center



Amaia Salvador

amaia.salvador@upc.edu

PhD Candidate

Universitat Politècnica de Catalunya



Santiago Pascual de la Puente

santi.pascual@upc.edu

PhD Candidate

Universitat Politècnica de Catalunya
Technical University of Catalonia

Lab created by



Míriam Bellver

miriam.bellver@bsc.edu

PhD Candidate

Barcelona Supercomputing Center



Today's objectives

- Tricks when working with small dataset
- Training network from scratch with and without data augmentation
- Using pretrained network just to extract features
- Using pretrained network and finetune it



Cats vs Dataset

- Cats vs. Dogs dataset
 - Binary Classification between cats and dogs
 - Does **not** come packaged with Keras



Google Colab

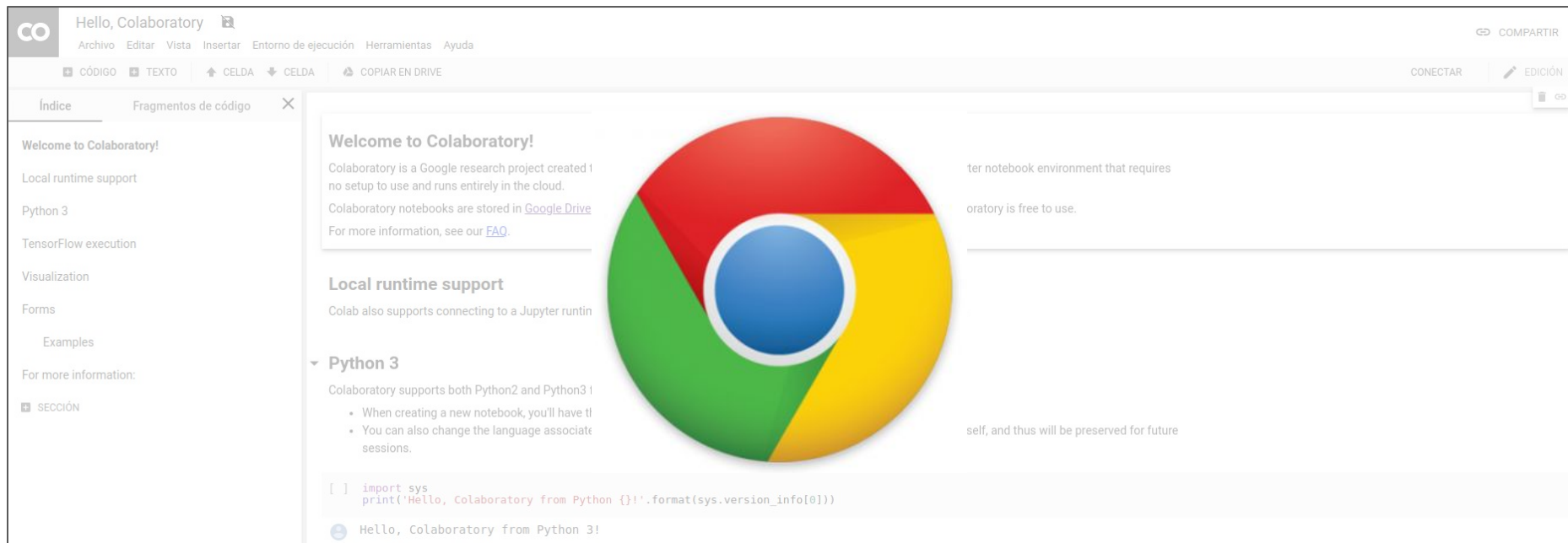
The screenshot displays the Google Colaboratory web interface. At the top, there's a header with the 'co' logo, the text 'Hello, Colaboratory', and a list of menu items: Archivo, Editar, Vista, Insertar, Entorno de ejecución, Herramientas, and Ayuda. On the right of the header are links for 'COMPARTIR', 'CONECTAR', and 'EDICIÓN'. Below the header is a toolbar with icons for 'CÓDIGO', 'TEXTO', 'CELDA', and 'COPIAR EN DRIVE'. A sidebar on the left contains a table of contents with links to 'Índice', 'Fragmentos de código', 'Welcome to Colaboratory!', 'Local runtime support', 'Python 3', 'TensorFlow execution', 'Visualization', 'Forms', 'Examples', and 'For more information:'. The main content area shows the 'Welcome to Colaboratory!' message, explaining that Colaboratory is a Google research project for disseminating machine learning education and research, and that notebooks are stored in Google Drive. It also mentions 'Local runtime support' and 'Python 3'. At the bottom, a code cell is shown with the following Python code:

```
[ ] import sys
    print('Hello, Colaboratory from Python {}'.format(sys.version_info[0]))
```

Below the code cell, the output is displayed: 'Hello, Colaboratory from Python 3!'.

<https://colab.research.google.com/>

Google Colab



The screenshot displays the Google Colaboratory web interface. At the top, the header includes the 'co' logo, the title 'Hello, Colaboratory', and a menu with options: Archivo, Editar, Vista, Insertar, Entorno de ejecución, Herramientas, and Ayuda. On the right, there are links for 'COMPARTIR' and 'CONECTAR', and a button for 'EDICIÓN'. Below the header, a toolbar shows icons for 'CÓDIGO', 'TEXTO', 'CELDA', and 'COPIAR EN DRIVE'. The left sidebar contains a table of contents with links to 'Índice', 'Fragmentos de código', 'Welcome to Colaboratory!', 'Local runtime support', 'Python 3', 'TensorFlow execution', 'Visualization', 'Forms', 'Examples', and 'For more information:'. The main content area features a large, colorful circular logo in the center. To the left of the logo, the 'Welcome to Colaboratory!' section explains that Colaboratory is a Google research project that runs entirely in the cloud and that notebooks are stored in Google Drive. Below this, the 'Local runtime support' section mentions connecting to a Jupyter runtime. The 'Python 3' section lists two bullet points: 'When creating a new notebook, you'll have to...' and 'You can also change the language associated with the notebook for future sessions.' At the bottom, a code cell shows a Python script that prints 'Hello, Colaboratory from Python 3!'. The output of the code cell is 'Hello, Colaboratory from Python 3!'.

co Hello, Colaboratory

Archivo Editar Vista Insertar Entorno de ejecución Herramientas Ayuda

CÓDIGO TEXTO CELDA CELDA COPIAR EN DRIVE

COMPARTIR CONECTAR EDICIÓN

Índice Fragmentos de código

Welcome to Colaboratory!

Colaboratory is a Google research project created in 2016. It is a free, no setup to use and runs entirely in the cloud. Colaboratory notebooks are stored in [Google Drive](#). For more information, see our [FAQ](#).

Local runtime support

Colab also supports connecting to a Jupyter runtime.

Python 3

Colaboratory supports both Python2 and Python3!

- When creating a new notebook, you'll have to...
- You can also change the language associated with the notebook for future sessions.

```
[ ] import sys
print('Hello, Colaboratory from Python {}'.format(sys.version_info[0]))
```

Hello, Colaboratory from Python 3!

<https://colab.research.google.com/>

Google Colab



1. Login in [Colab](#) with a Google account: yours or aidlupc2019@gmail.com (talentcenter)
2. Open [the notebook](#) of this lab session
3. Copy this notebook to your Drive to be able to run it (or open in draft mode if using aidlupc2019@gmail.com)
4. Change runtime type to work with GPU! Your trainings will be much faster :)

aidl2019_dl_lab4_transfer.ipynb

File Edit View Insert Runtime Tools Help

CODE TEXT CELL

```
import keras
keras.__version__
import numpy as np
```

Transfer Learning

In this session we will work with convolutional neural networks, when dealing with small datasets, which is a very usual situation, as data can be difficult to obtain certain scenarios, specially labelled data.

Downloading the database

During this lab session, we will work with a small database of images with dogs and cats. The cats vs. dogs dataset that we will use isn't packaged with Keras. It was made available by Kaggle.com as part of a computer vision competition in late 2013, back when convnets weren't quite mainstream.

The following command line will download to your remote machine the Kaggle database that we will need for this lab session. It will take a few seconds.

```
[ ] !wget https://transfer.sh/148a8m/train.zip
```

Now you will need to unzip the database that you have just downloaded, with the following line:

Notebook settings

Runtime type
Python 3

Hardware accelerator
GPU

☐ Omit code cell output when saving this notebook

CANCEL SAVE

Final Questions

Undergradese

What undergrads ask vs. what they're REALLY asking

"Is it going to be an open book exam?"

Translation: "I don't have to actually memorize anything, do I?"

"Hmm, what do you mean by that?"

Translation: "What's the answer so we can all go home."

"Are you going to have office hours today?"

Translation: "Can I do my homework in your office?"

"Can i get an extension?"

Translation: "Can you re-arrange your life around mine?"

"Is this going to be on the test?"

Translation: "Tell us what's going to be on the test."

"Is grading going to be curved?"

Translation: "Can I do a mediocre job and still get an A?"

JORGE CHAM © 2008



WWW.PHDCOMICS.COM