VisRec Tutorial
Session 1: Introduction

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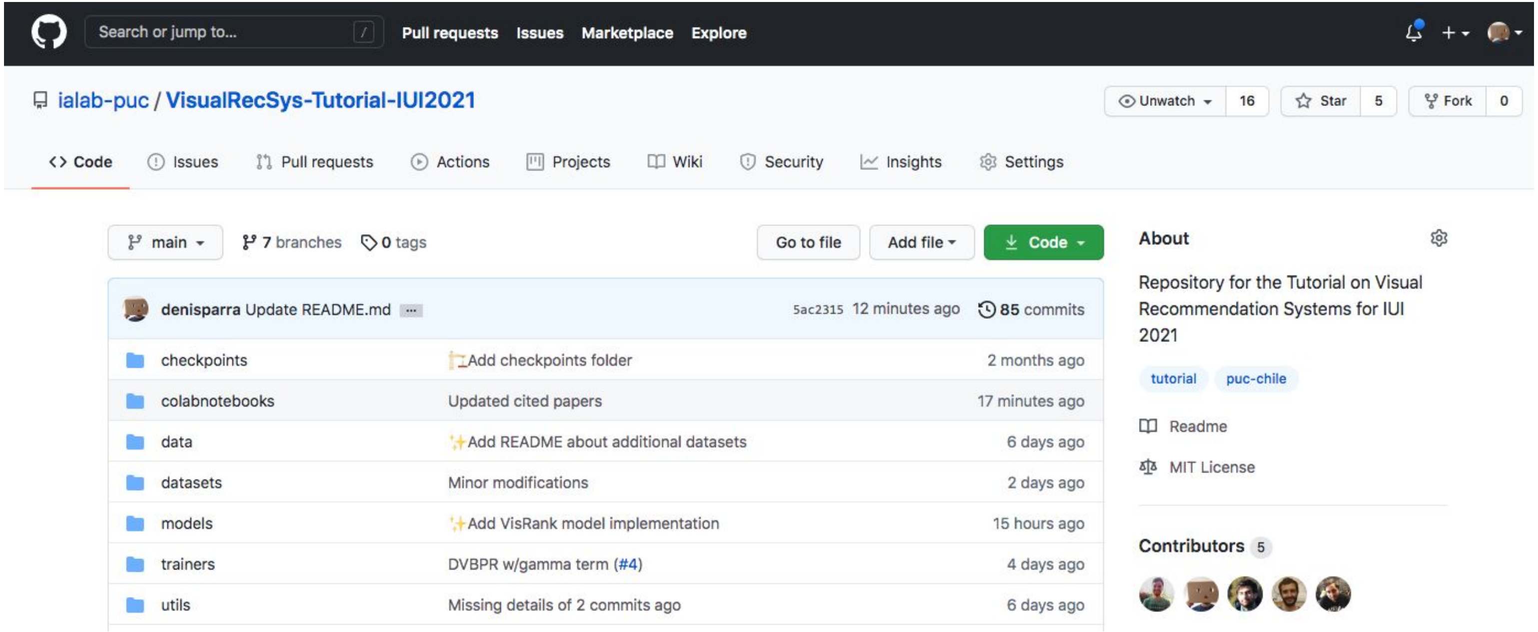
26th ACM Conference on Intelligent User Interfaces

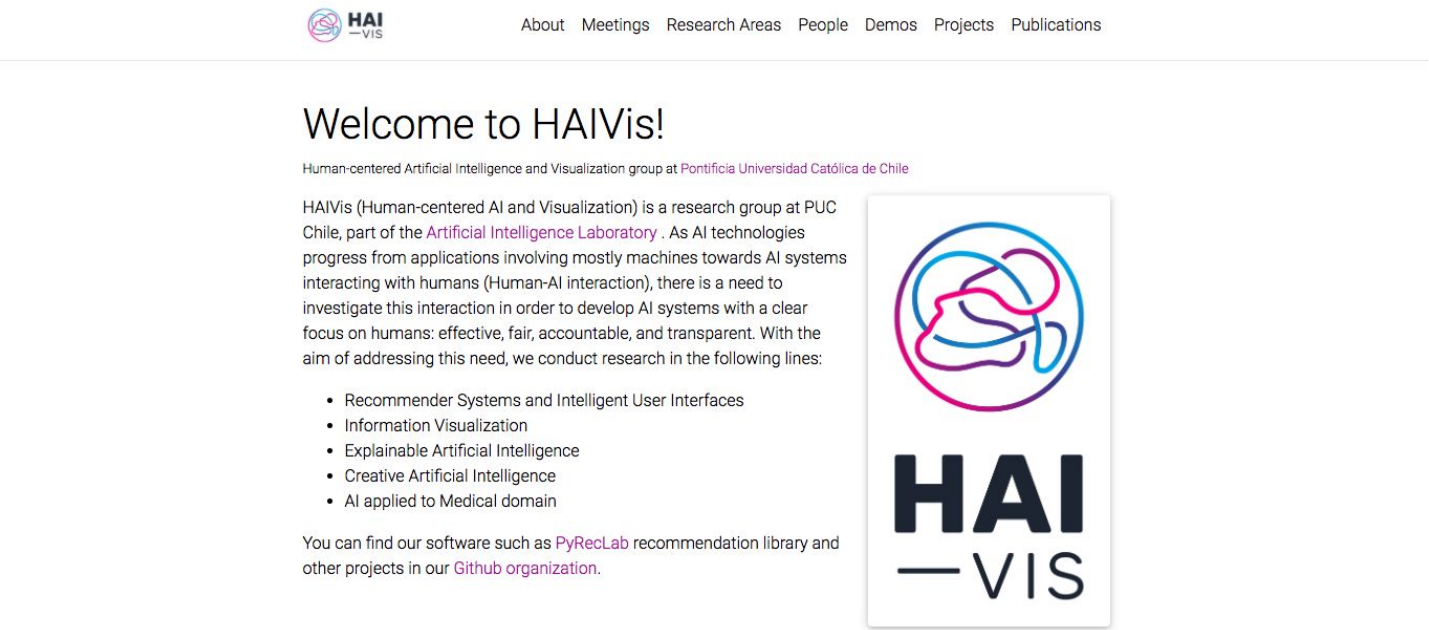
Tutorial Web site

https://github.com/ialab-puc/VisualRecSys-Tutorial-IUI2021



We are launching our HAIVis group’s website !

https://haivis.ing.puc.cl/


About Meetings Research Areas People Demos Projects Publications

Welcome to HAIVis!

Human-centered Artificial Intelligence and Visualization group at Pontificia Universidad Católica de Chile

HAIVis (Human-centered AI and Visualization) is a research group at PUC Chile, part of the Artificial Intelligence Laboratory . As AI technologies progress from applications involving mostly machines towards AI systems interacting with humans (Human-AI interaction), there is a need to investigate this interaction in order to develop AI systems with a clear focus on humans: effective, fair, accountable, and transparent. With the aim of addressing this need, we conduct research in the following lines:

- Recommender Systems and Intelligent User Interfaces
- Information Visualization
- Explainable Artificial Intelligence
- Creative Artificial Intelligence
- AI applied to Medical domain

You can find our software such as PyRecLab recommendation library and other projects in our Github organization.

Tutorial Table of Contents (Starting at 1:30PM CDT)

(40 mins) **Session 1**: Introduction to Visual RecSys, datasets and feature extraction with CNNs in Pytorch

(40 mins) **Session 2**: Pipeline for training and testing visual RecSys in Pytorch, application with VisRank and VBPR

(10 mins) [BREAK]

(25 mins) **Session 3**: Dynamic Visual Bayesian Personalized Ranking (DVBPR) in Pytorch

(25 mins) **Session 4**: CuratorNet in Pytorch

(25 mins) **Session 5**: Attentive Collaborative Filtering (ACF) in Pytorch

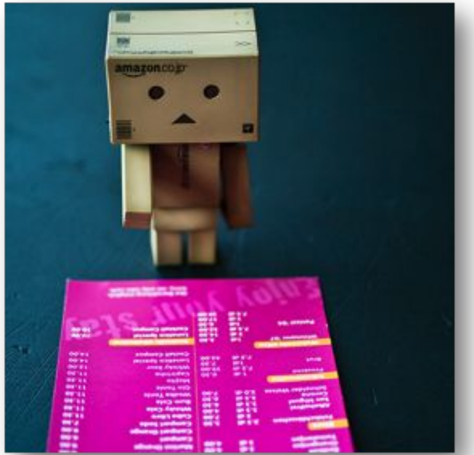
[BREAK]

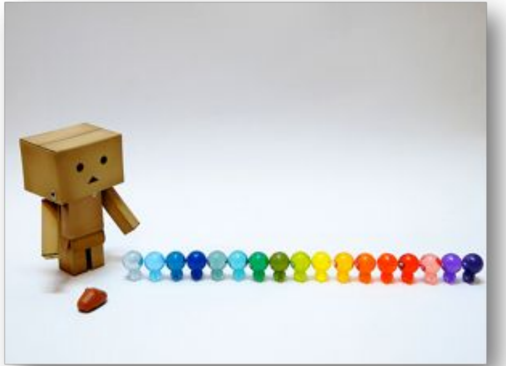
(10 mins) **Conclusion**

Session 1: Table of Contents

Recommender Systems

Systems that help (groups of) people to find relevant items in a crowded item or information space (MacNee et al. 2006)





http://www.flickr.com/photos/dongga/4597533223/sizes/m/

http://www.flickr.com/photos/meaganmakes/6769496875/sizes/m/

Types of Recommender Systems

Without covering all possible methods, the two most typical classifications on recommender algorithms are:

Classification 1	Classification 2
- Collaborative Filtering - Content-based Filtering - Hybrid	- Memory-based - Model-based

Types of Recommender Systems

In this tutorial, we are focusing on these:

Classification 1	Classification 2
- Collaborative Filtering - **Content-based Filtering** - **Hybrid**	- Memory-based - **Model-based**

Motivation

Why this Tutorial on Visual Recommendation Systems?

- **Increasing growth of multimedia usage on the Web** (Images, Video)

  Facebook (2004), Twitter (2006), **Pinterest** (2010), **Instagram** (2010), **TikTok** (2016)

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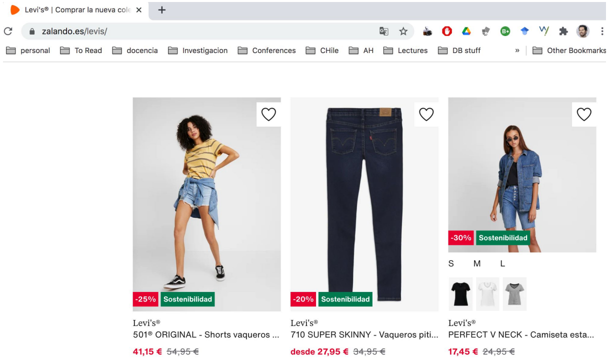
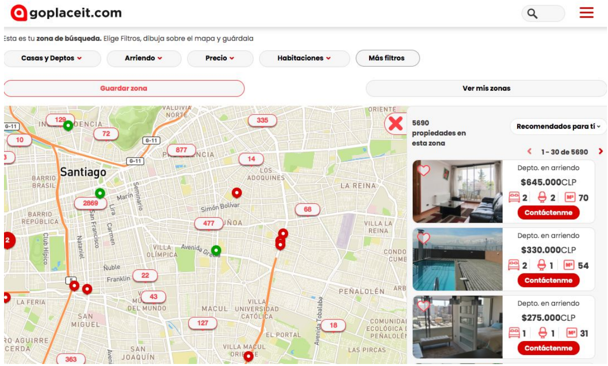
- **Increasing use of multimedia for e-commerce applications** (fashion, tourism, real estate) e.g. Zalando, goplaceit





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- **Increasing performance of visual features obtained from Deep Learning methods for related tasks (2012 - ...)**

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- Increasing performance of visual features obtained from Deep Learning methods for related tasks (2012 - ...)

- **Growing potential of transfer learning** (2012 - ...)

Computer Vision: Historical Datasets

- 1996: faces and cars 14,000 images of 10,000 people
- 1998: MNIST 70,000 images of handwritten digits
- 2004: Caltech 101, 9,146 images of 101 categories
- 2005: PASCAL VOC 20,000 images with 20 classes

Imagenet dataset

- Imagenet [0]: Presented in 2009 at CVPR

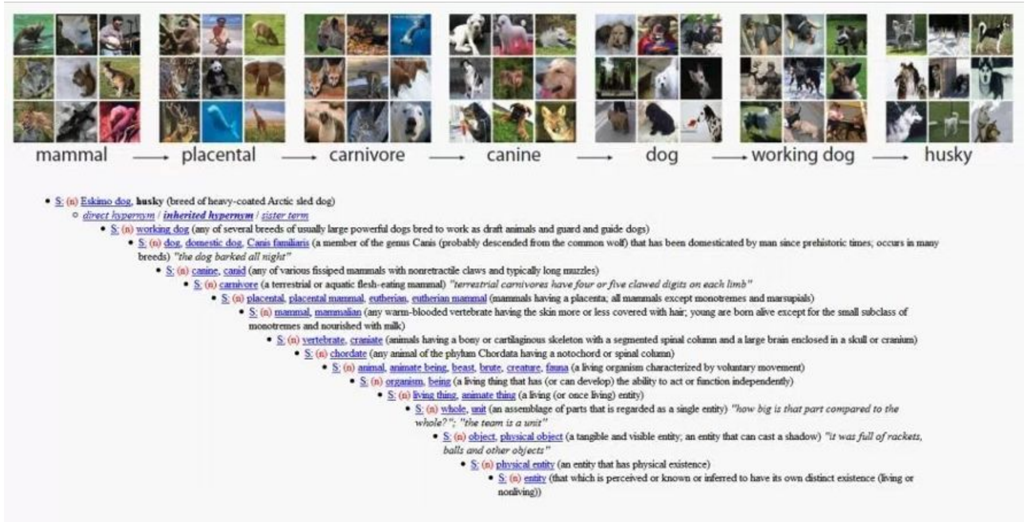
IMAGENET Large Scale Visual Recognition Challenge

- Crowdsourced
- 14,197,122 images

- 21,841 categories (non-empty synsets)
- Categories based on ***WordNet*** taxonomy

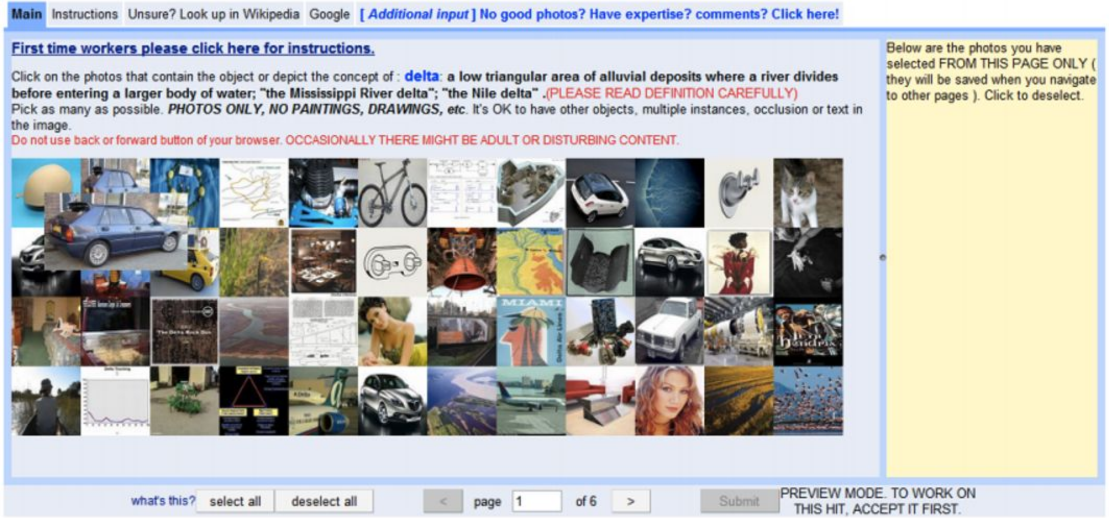
WordNet

- Wordnet: Miller’s project started in 1980 at Princeton, a hierarchy for the English language
- **Prof. Fei-Fei Li** (UIUC, Princeton, Stanford), worked on filling WordNet with many images.



Imagenet: Crowdsourced

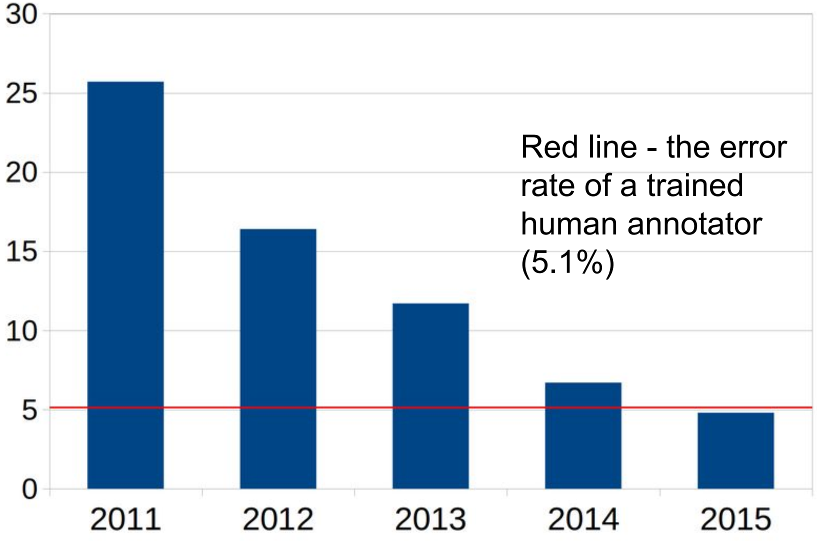
- Amazon Mechanical Turk
- It took 2.5 years to complete.
- Originally 3.2 million images in 5,247 categories (mammal, vehicle, etc.)



Imagenet Challenge

- The dataset was used to set a competition for image classification.

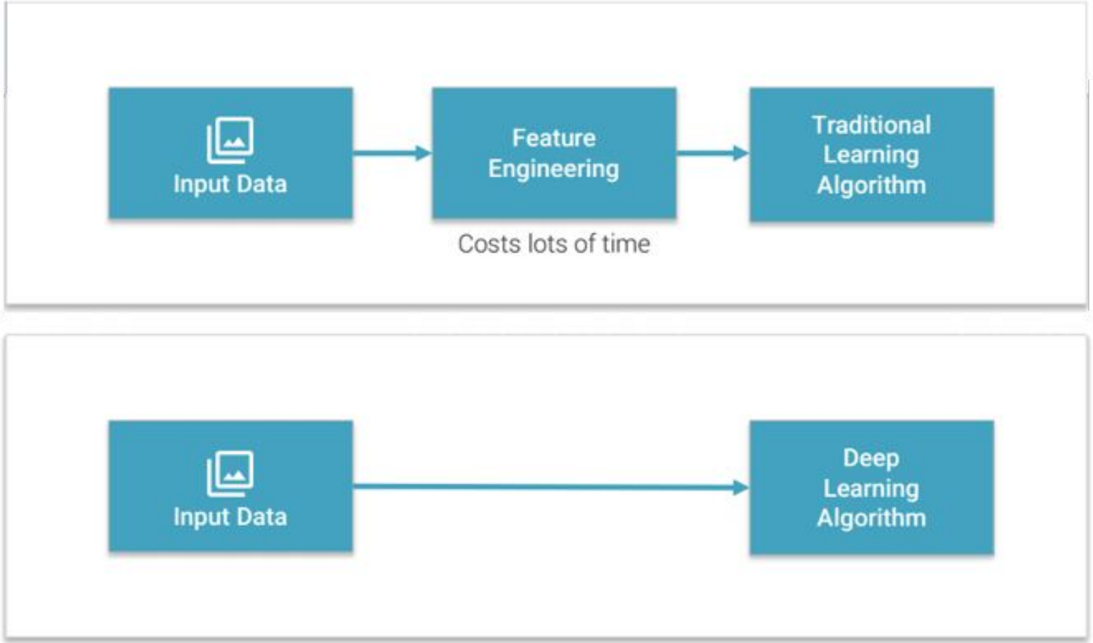
- In **2012 a team used deep learning, got error rate below 25%** (Hinton et al.), 10.8 point margin, 41% better than next best.



Progress in machine classification of images: the error rate (%) of the ImageNet competition winner by year.

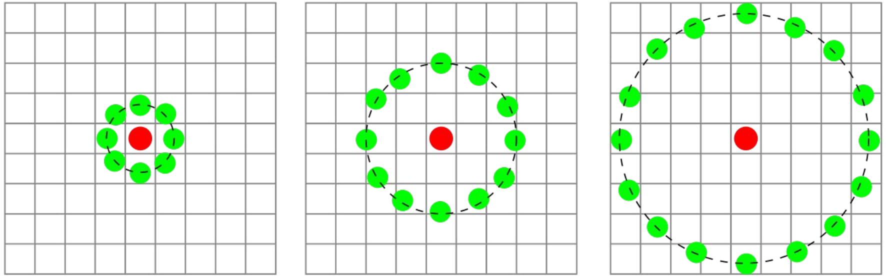
Deep Neural Networks: Representation Learning

Deep learning makes a great revolution not only in performance, but also on representation learning



Computer Vision: Historical Feature Extraction

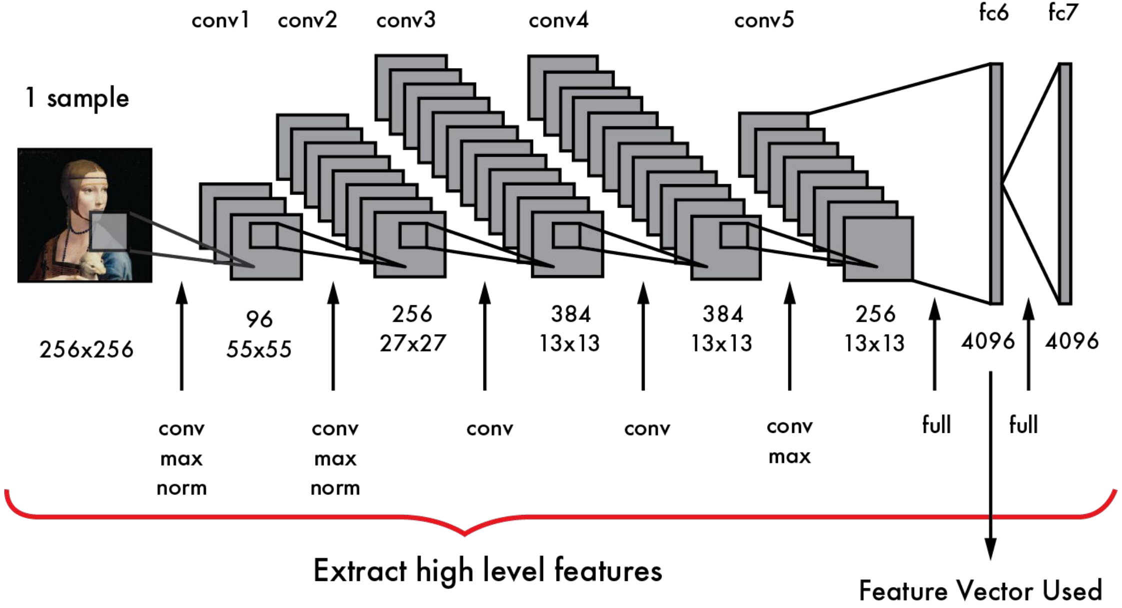
- **[1] LBP**: Local Binary Patterns
- **[2] HOG**: Histogram of Oriented Gradients
- **[3] SIFT**: scale-invariant feature transform



Deep Neural Networks: Representation Learning

AlexNet [4] made a great revolution not only in performance, but also on representation learning

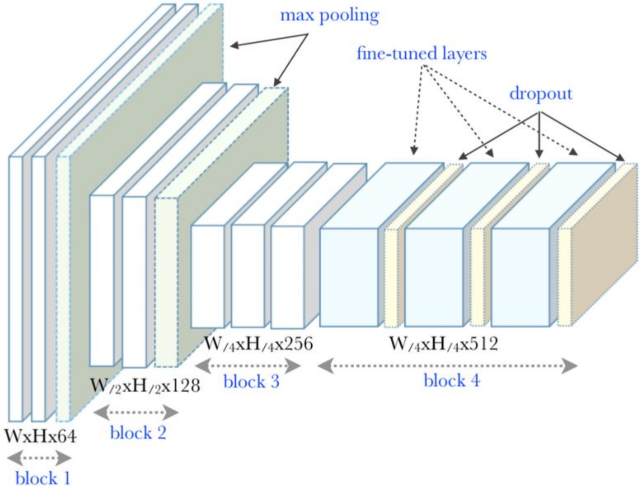
Aprox 60 million parameters



Deep Neural Networks in Computer Vision

VGG [5] introduced by the Visual Geometry Group at Oxford University, increases network depth by using very small convolution filters (3x3) compared to AlexNet. There are different versions depending on the number of layers (VGG-16/19)

Aprox 138 million parameters



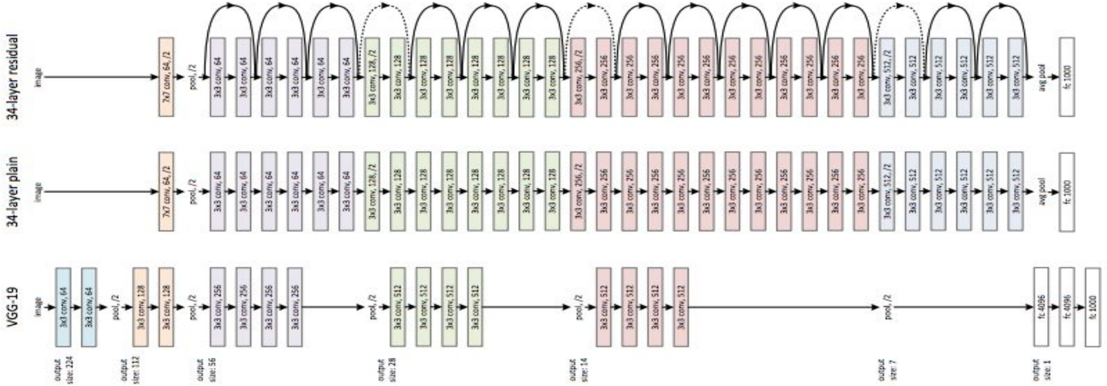
Deep Neural Networks in Computer Vision

ResNet [6] introduces a residual learning framework to ease the training of networks that are substantially deeper than those used previously (AlexNet, VGG)

ResNet-18 Aprox. 11 million parameters

method	top-1 err.	top-5 err.
VGG [40] (ILSVRC'14)	-	8.43†
GoogLeNet [43] (ILSVRC'14)	-	7.89
VGG [40] (v5)	24.4	7.1
PReLU-net [12]	21.59	5.71
BN-inception [16]	21.99	5.81
ResNet-34 B	21.84	5.71
ResNet-34 C	21.53	5.60
ResNet-50	20.74	5.25
ResNet-101	19.87	4.60
ResNet-152	**19.38**	**4.49**

Table 4. Error rates (%) of **single-model** results on the ImageNet validation set (except † reported on the test set).

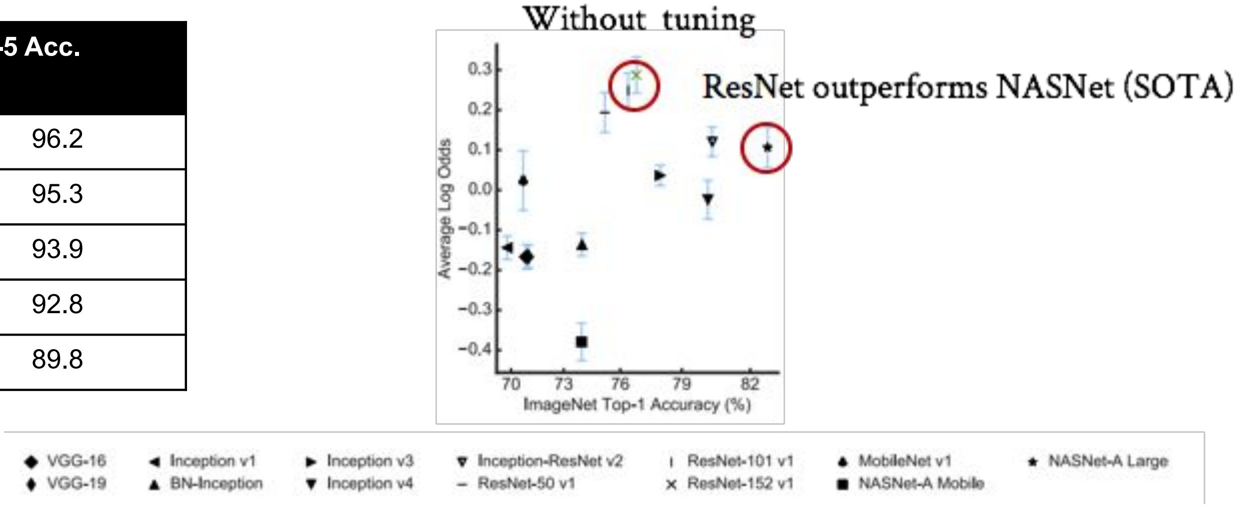


What about transfer learning?

Simon Kornblith, Jonathon Shlens, and Quoc V. Le. 2018. Do Better ImageNetModels Transfer Better? (2018). https://arxiv.org/abs/1805.08974

Method	Top-1 Acc	Top-5 Acc.
NASNet Large	82.7	96.2
InceptionResNetV2	80.4	95.3
InceptionV3	78.0	93.9
ResNet50	75.6	92.8
VGG19	71.1	89.8

https://github.com/tensorflow/models/tree/master/research/slim#pre-trained-models



What about transfer learning for Visual RecSys?

Using pre-trained neural networks, there is not correlation between Imagenet and image recsys performance [7].

CNN	Artwork Image Recommendation				ILSVRC-2012-CLS	
	R@20	P@20	MRR@20	nDCG@20	Top-1 Acc. (%)	Top-5 Acc. (%)
ResNet50	**.1632**	**.0141**	**.0979**	**.1253**	75.2	92.2
VGG19	**.1398**	**.0124**	**.0750**	**.1008**	71.1	89.8
NASNet Large	.1379	.0120	.0743	.0998	**82.7**	**96.2**
InceptionV3	.1332	.0125	.0744	.1007	78.0	93.9
InceptionResNetV2	.1302	.0117	.0692	.0936	**80.4**	**95.3**
Random	.0172	.0013	.0051	.0093	-	-

Datasets for Visual Recommender Systems

Is there a Movielens dataset to train and benchmark visual recommendation systems ?

Datasets for Visual Recommender Systems

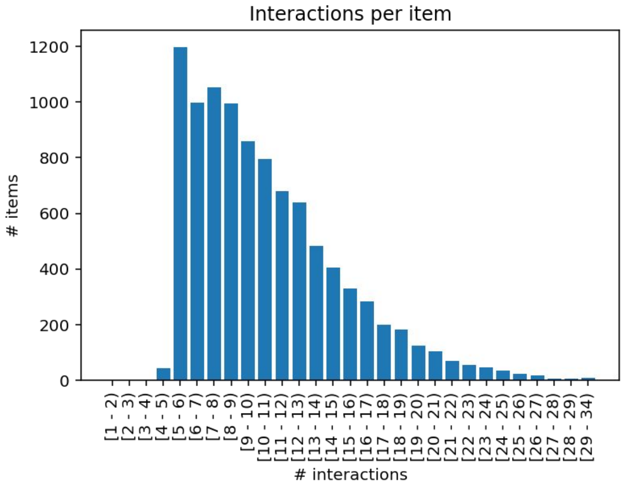
Is there a Movielens dataset to train and benchmark visual recommendation systems ?

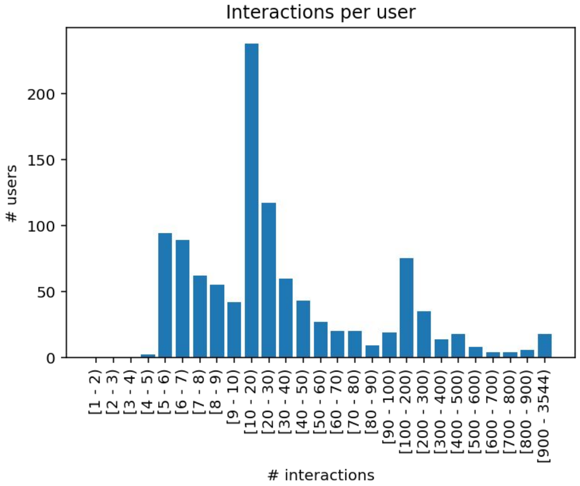
Not exactly. There are some datasets, but usually you find embeddings (npy files) but not images, or the URL to files you need to download on your own

- https://cseweb.ucsd.edu/~jmcauley/datasets.htm (Behance, Amazon)
- Pinterest, mongoDB dataset (https://goo.gl/LjMoYa)
- UGallery (provided by us at https://github.com/ialab-puc/CuratorNet)

The Wikimedia Commons Dataset

- Thanks to support by Diego Saez from Wikimedia Foundation
- We share a sample for the community
  - 1,079 unique users / 9,636 unique items / 96,991 interactions

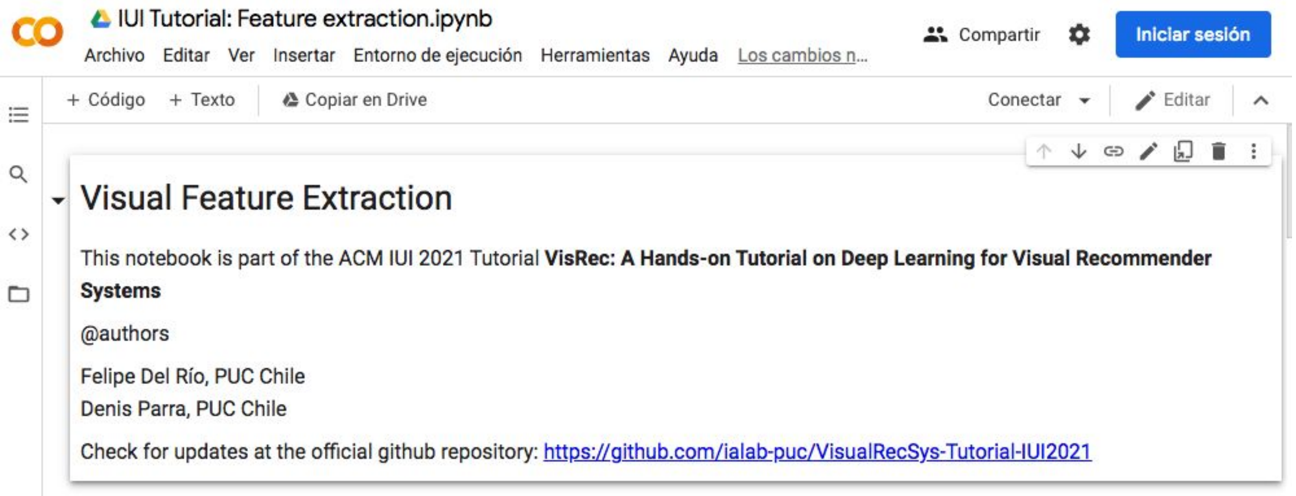




Hands-on Session

https://colab.research.google.com/drive/1JCTPS88AzKA0KNVCoEvYCBaaYebgdoYn?usp=sharing or

https://bit.ly/3g7nLVI



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[3] Lowe, D. G. (1999). Object recognition from local scale-invariant features. In Proceedings of the seventh IEEE international conference on computer vision (Vol. 2, pp. 1150-1157).

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VisRec: A Hands-on Tutorial on Deep Learning for Visual Recommender Systems

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