人工智能导论

李文
计算机科学与工程学院

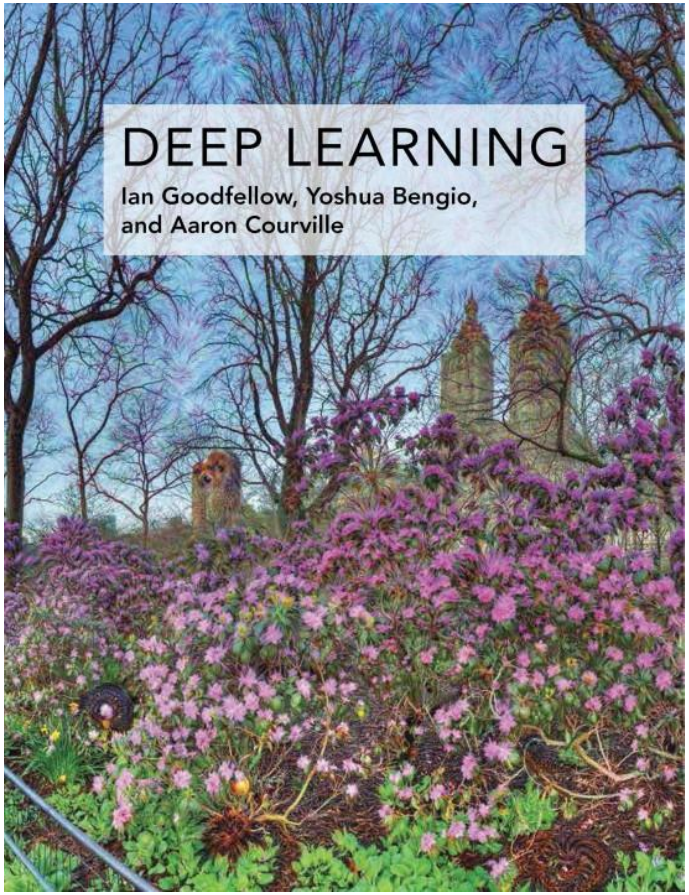
数据智能研究组（Data Intelligence Group）：
http://dig.uestc.cn/

01 对抗生成网络

Generative Adversarial Networks (GAN)

Generative Adversarial Networks (GAN)

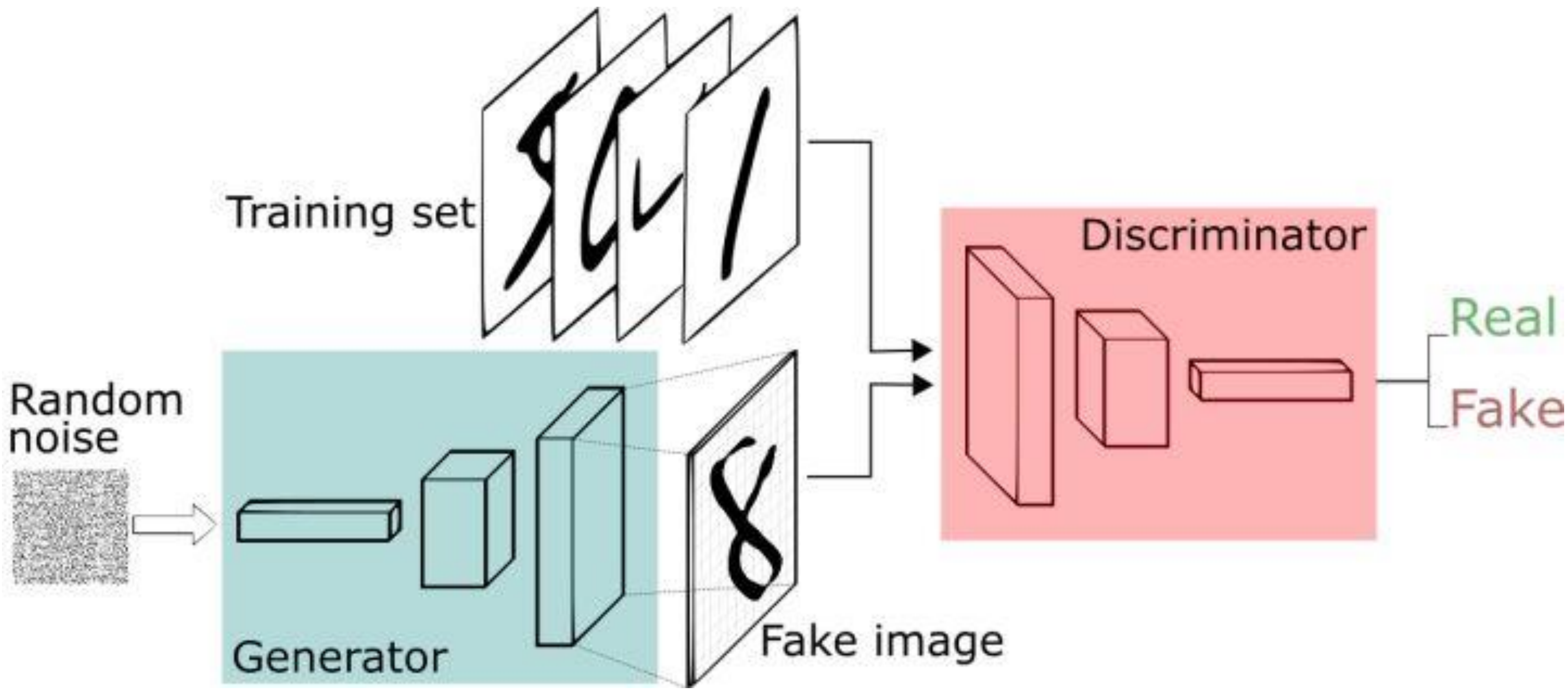
- 发明人
  - Ian Goodfellow



Goodfellow, Ian J., Pouget-Abadie, Jean, Mirza, Mehdi, Xu, Bing, Warde-Farley, David, Ozair, Sherjil, Courville, Aaron C., and Bengio, Yoshua. Generative adversarial nets. NIPS, 2014.

Generative Adversarial Networks (GAN)

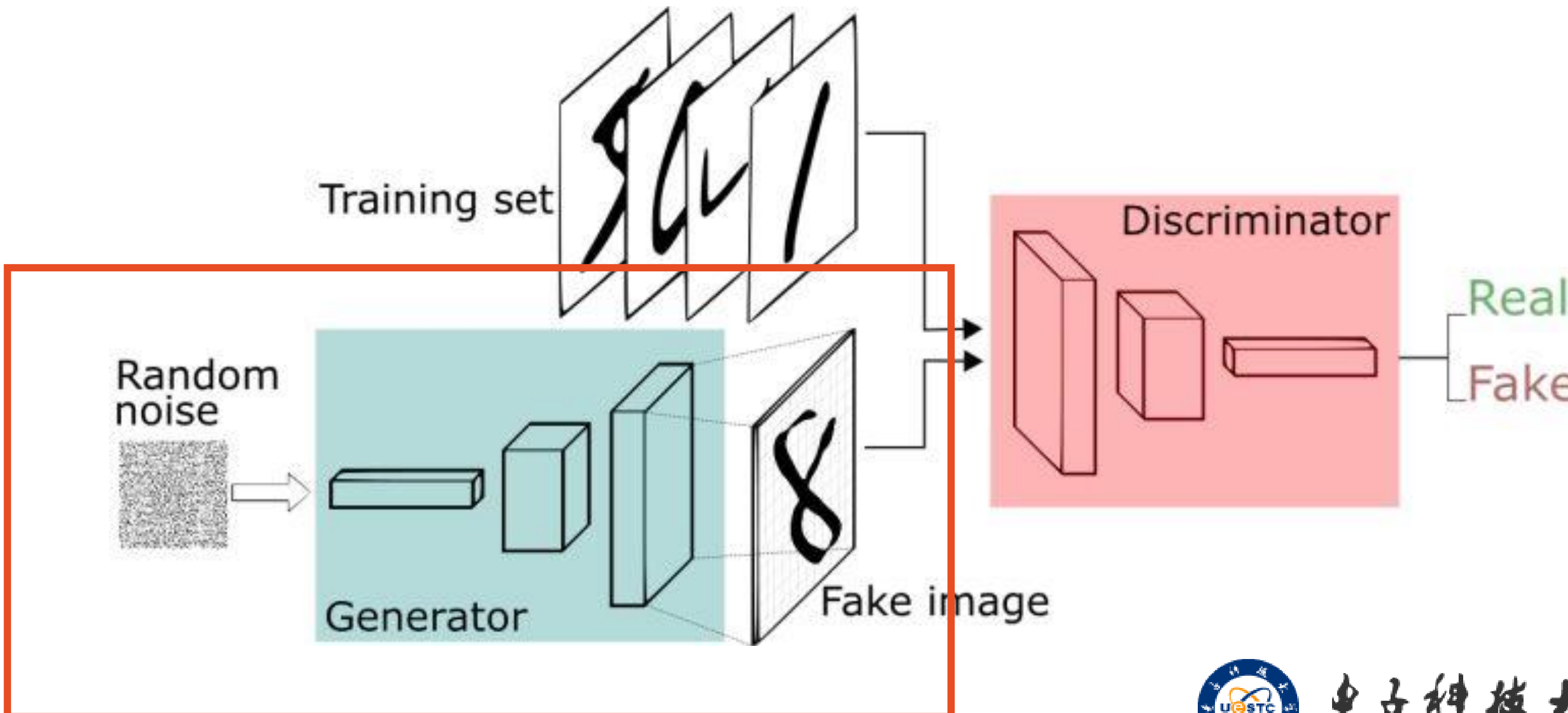
- 关键字：对抗生成网络
  - 判别器和生成器互相竞争，以期实现不断提高



Generative Adversarial Networks (GAN)

■关键字：对抗生成网络

●生成：给定数据$\mathcal{X}$，来学习一个映射f，从参数空间θ映射到样本空间$\mathcal{X}$



Generative Adversarial Networks (GAN)

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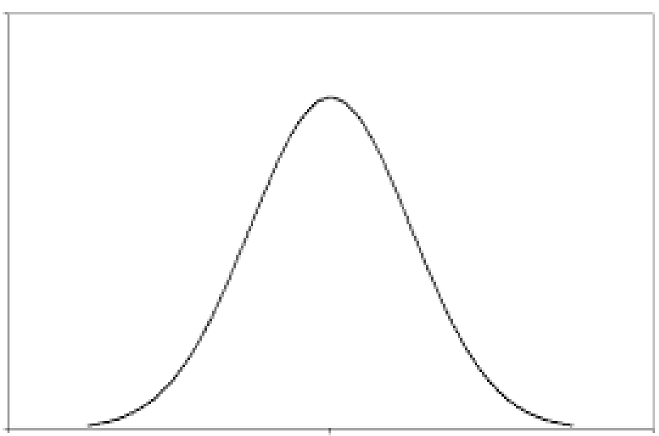
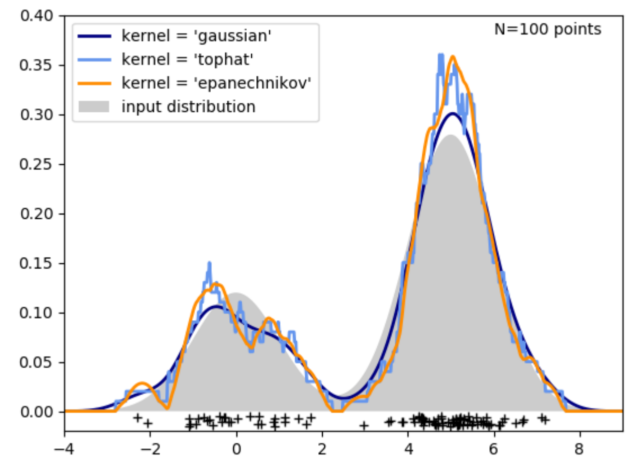


θ



$\mathcal{X}$

从一个先验分布（高斯）映射到实际数据的分布

Generative Adversarial Networks (GAN)

■关键字：对抗生成网络

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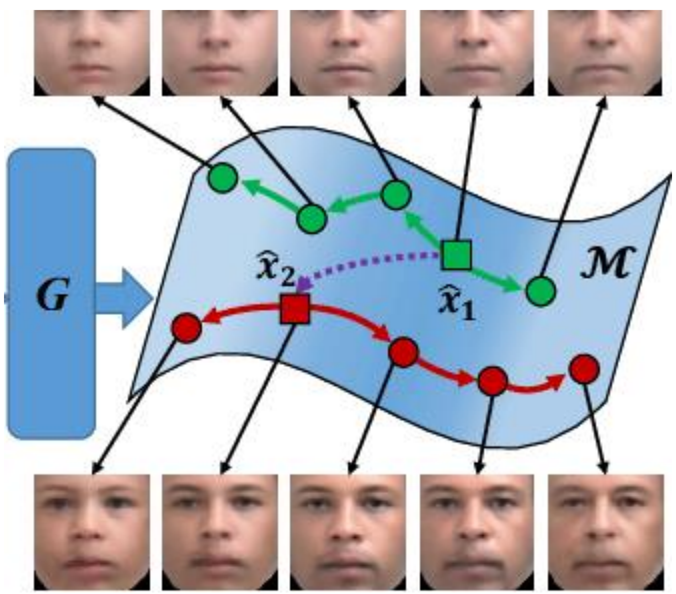
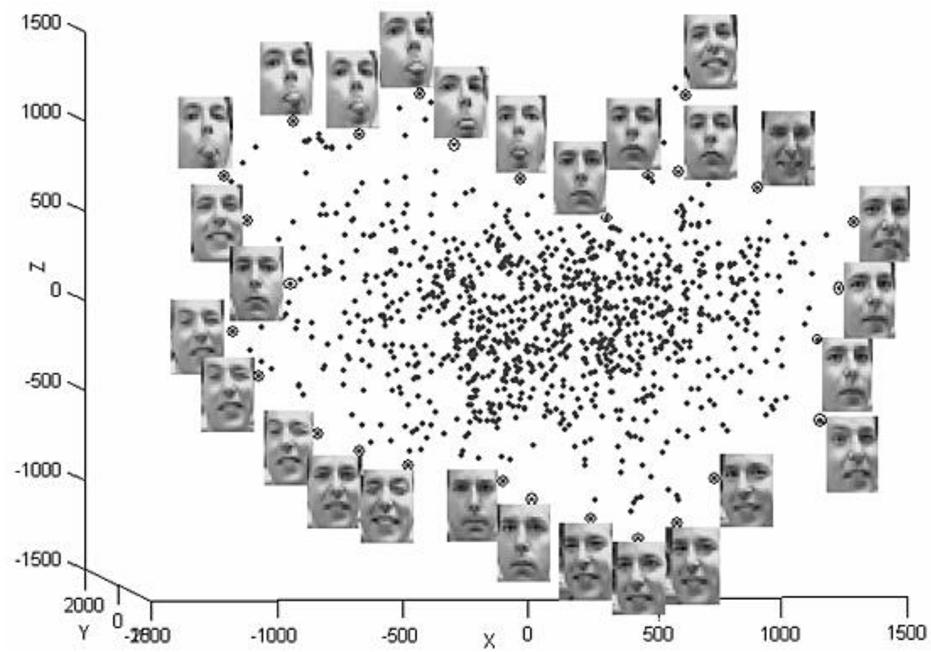




图像映射到一个低维空间，形成有意义的编码（特征）

Generative Adversarial Networks (GAN)

- loss如何设计？分布之间的差异
  - 判别器：区分fake和real

$$H((x_i, y_i)_{i=1}^{N}, D) = -\sum_{i=1}^{N} y_i \log D(x_i) - \sum_{i=1}^{N} (1 - y_i) \log(1 - D(x_i))$$

  - 生成器：对抗判别器

$$\min_G \max_D V(D, G) = \mathbb{E}_{\boldsymbol{x} \sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z} \sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$$

Generative Adversarial Networks (GAN)

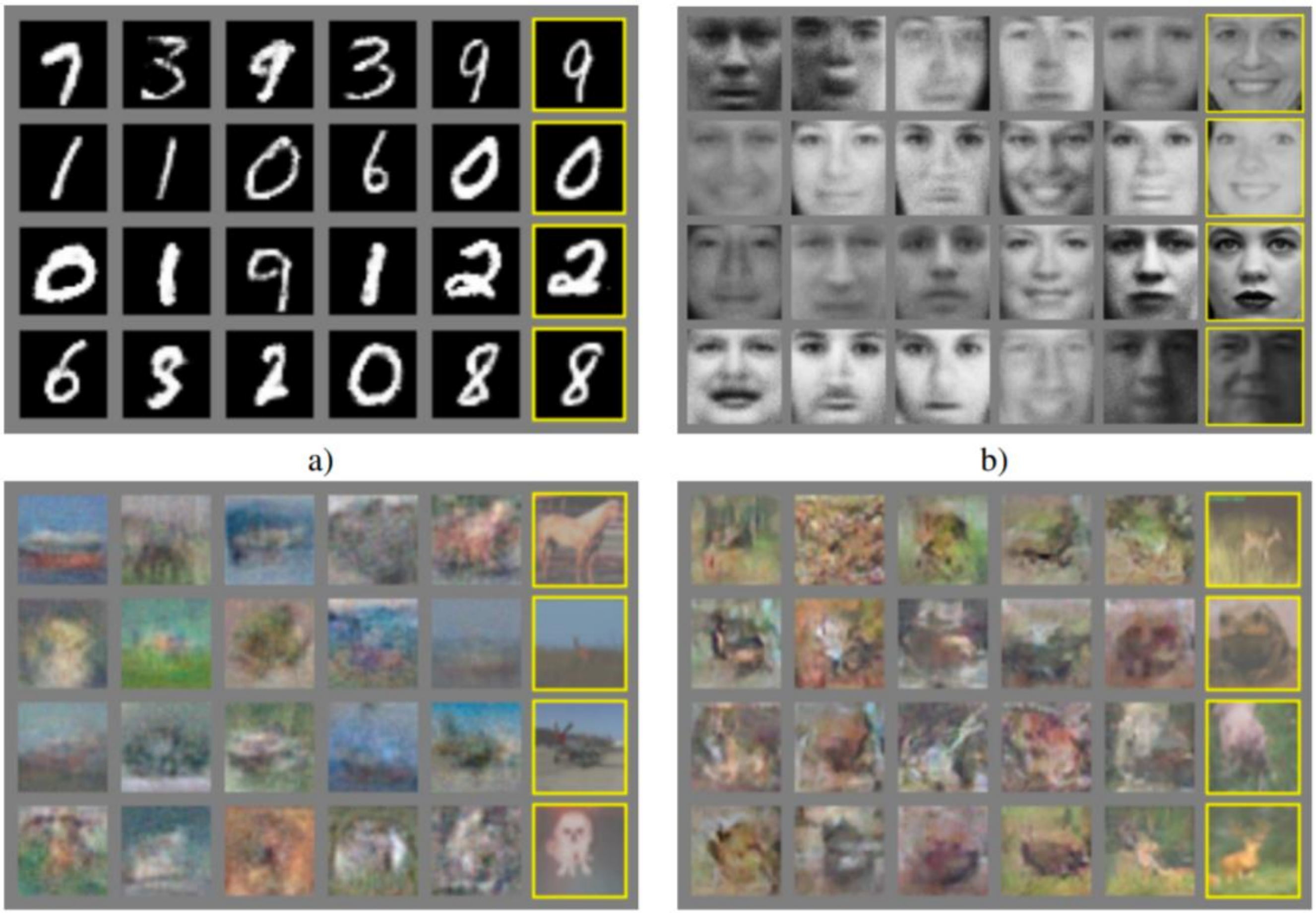
■训练

- ●1. 随机产生输入，生成fake的图像
- ●2. 随机real图像，和fake图像一起训练判别器
- ●3. 重复1-2若干次
- ●4. 更新生成器（switch fake图像的标签）
- ●5. 重复1-4若干次

$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$$

Generative Adversarial Networks (GAN)

■效果



a) b) c) d)

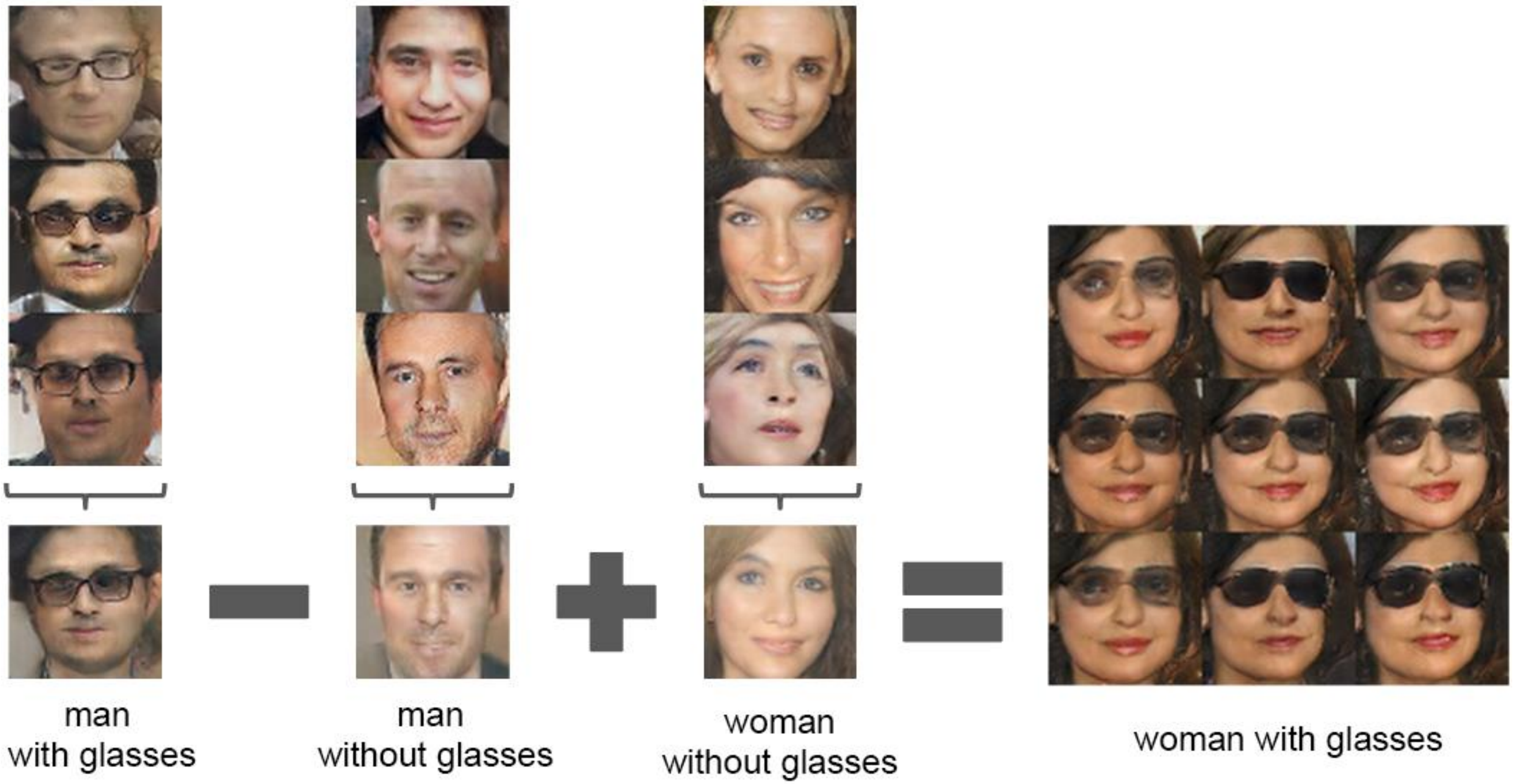
Goodfellow, Ian J., Pouget-Abadie, Jean, Mirza, Mehdi, Xu, Bing, Warde-Farley, David, Ozair, Sherjil, Courville, Aaron C., and Bengio, Yoshua. Generative adversarial nets. NIPS, 2014.

Generative Adversarial Networks (GAN)

■效果

Alec Radford, Luke Metz, Soumith Chintala. Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks. Arxiv 1511.06434, 2015.

Generative Adversarial Networks (GAN)



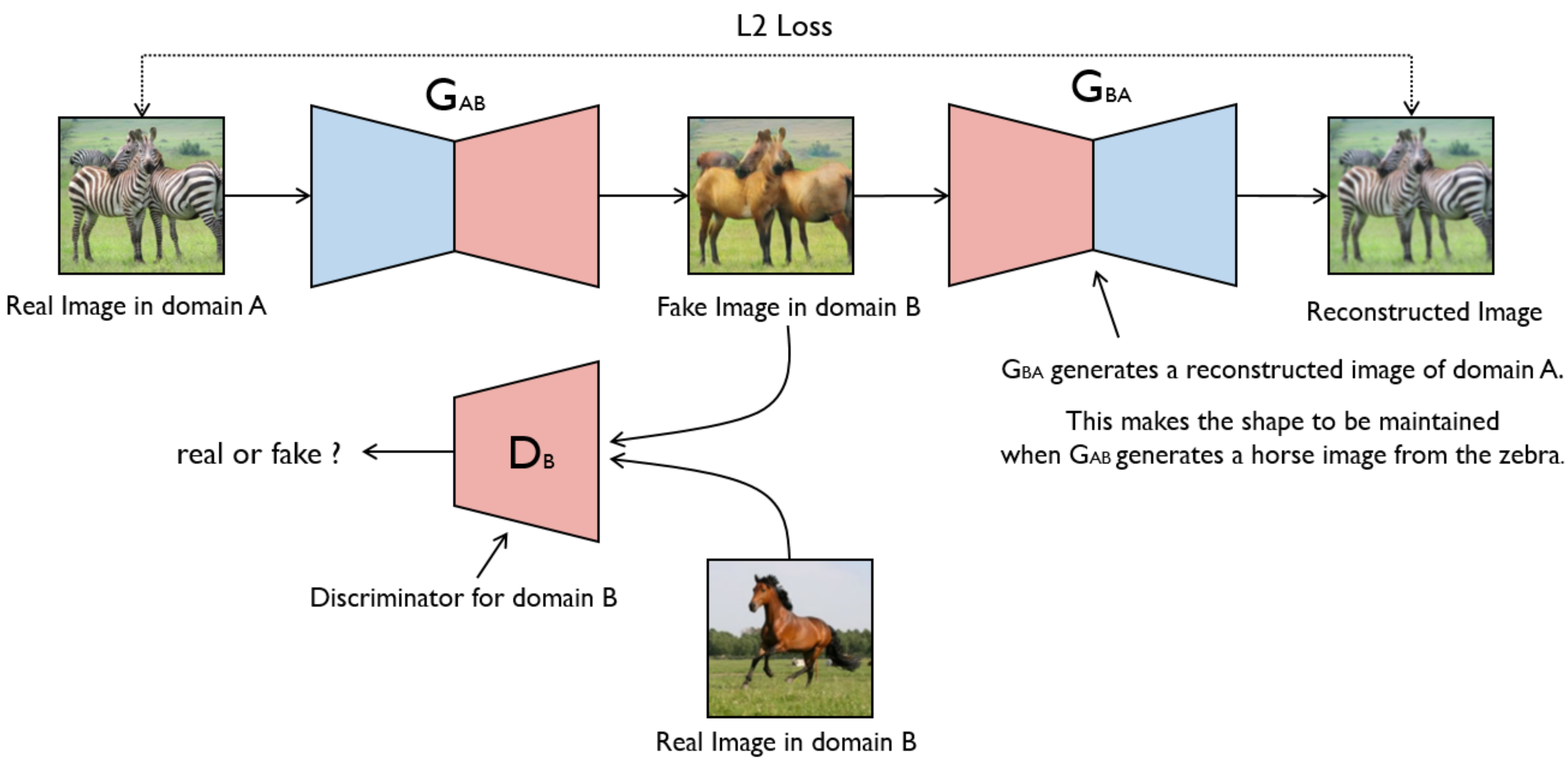
Alec Radford, Luke Metz, Soumith Chintala. Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks. Arxiv 1511.06434, 2015.

Generative Adversarial Networks (GAN)

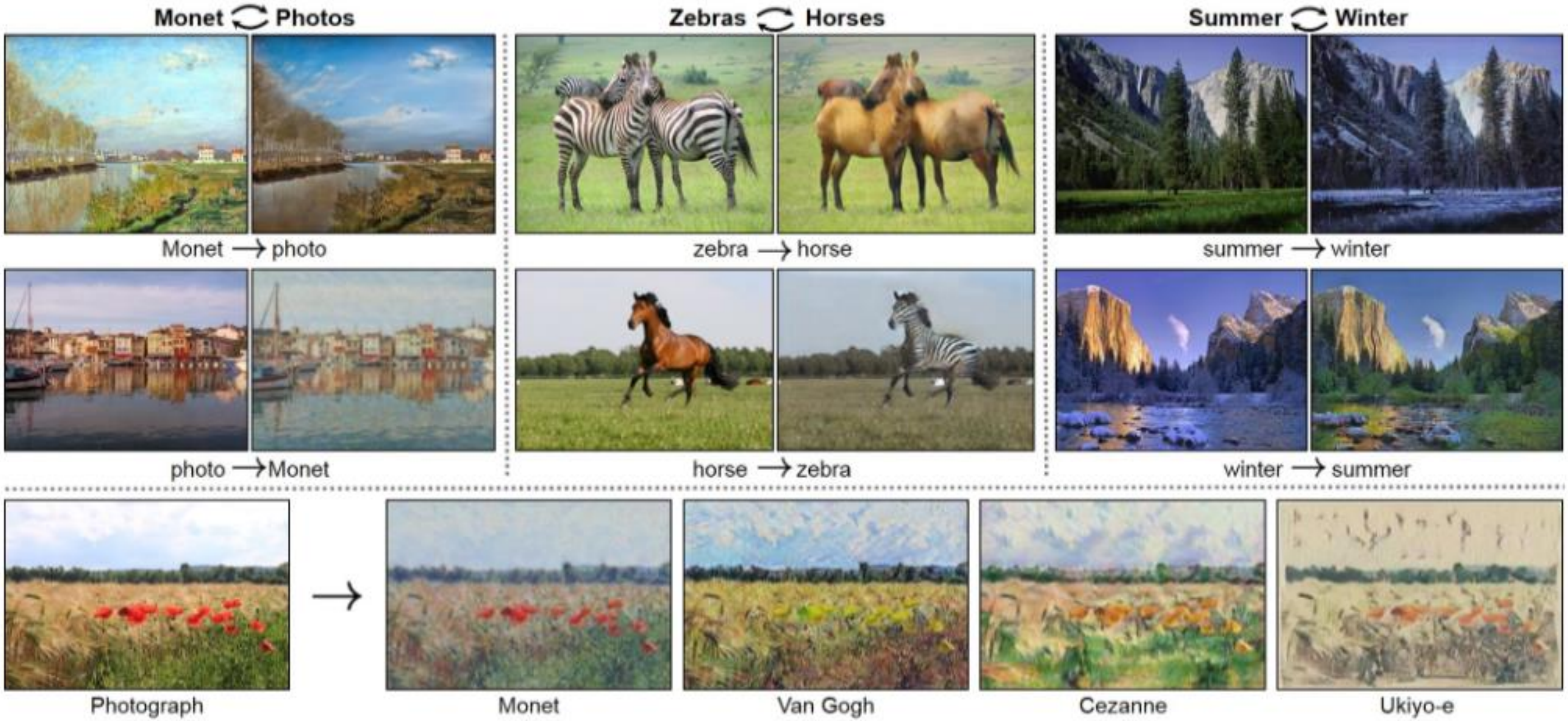
- BIGGAN

CycleGAN

■从图片到图片



CycleGAN



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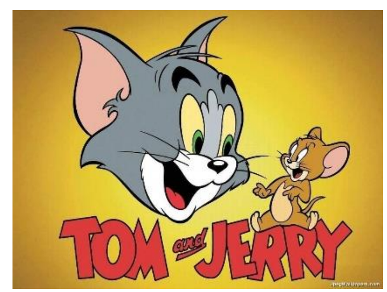
02 迁移学习

迁移学习

- Goal: To apply existing domain knowledge to the learning of a new domain
- 举例
  - C++学到的OOP用于辅助Java学习
  - 基于真实物体的认知去理解卡通物体



深度学习的数据困境

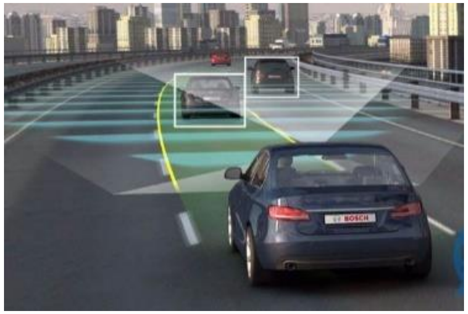
深度学习的数据困境

- We have met quite a few applications….

Surveillance

Face recognition
Vehicle recognition
Object re-ID
Illegal turning/parking
Driver behavior det.
…

Self-driving



Traffic sign recognition
Pedestrian detection
Car detection
Semantic segmentation
Distance estimation
…

Robotics

Object detection
Object recognition
3D detection/recog.
Image processing
…

Product Search

Image recognition
Object detection
Object recognition
Attribute recognition
Attribute generation
…

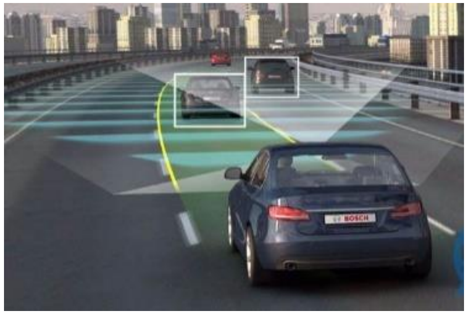
深度学习的数据困境

- We have met quite a few applications **in real scenarios**

Surveillance

Image quality diff. (Resolution, noise)
Surrounding env. (diff. countries)

Self-driving



Diff. weather (sunny, rainy, etc.)
Surrounding env. (diff. countries)

Robotics

Object detection
Object recognition
3D detection/recog.
Image processing
…

Product Search

Image recognition
Object detection
Object recognition
Attribute recognition
Attribute generation
…

深度学习的数据困境

- How to deal with that?
  - Intuitively: just get more annotations, well… from humans
  - Enough money and time…

Get enough budget $$$ → Outsource the labeling task and rest… → Have obtained sufficient labeled images → Deep learning models

人工智能：有多少人工就有多少智能…

深度学习的数据困境

- Cameras
  - DSLR: Nikon, Cannon, Sony, ...
  - Phones: iPhone, Samsung, Huawei, Xiaomi, ...
  - WebCams, DashCams, Notebooks, Kinects, ...





深度学习的数据困境

■Autonomous Driving

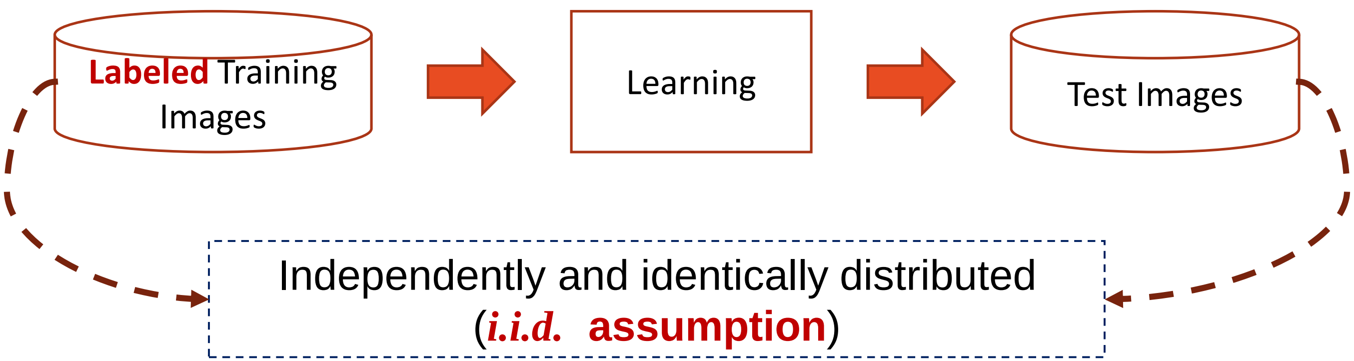
- Summer, Winter, Raining, Foggy, Night…






深度学习的数据困境

- Visual Recognition System

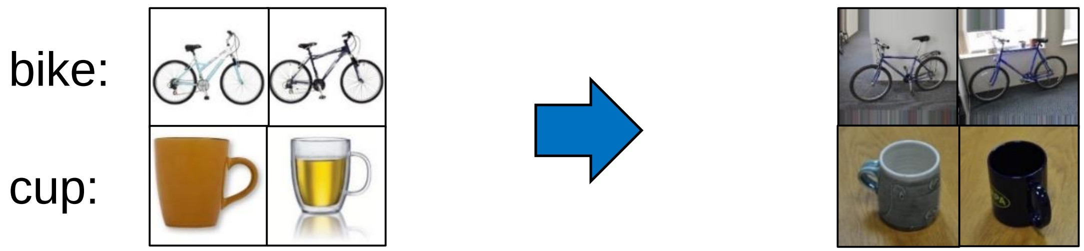


- “*i.i.d*” assumption hardly holds in real world applications

迁移学习之领域适应

Domain Adaptation

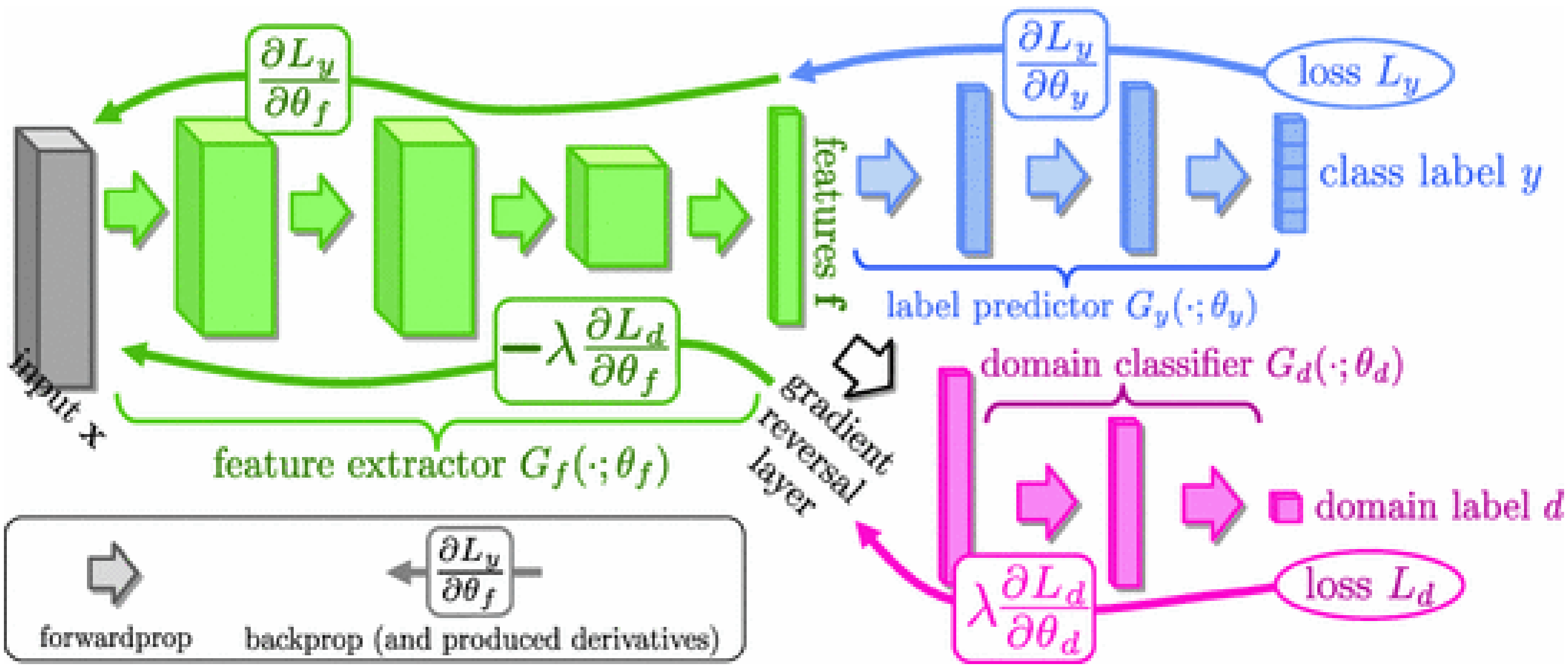
- A **labeled** source domain + an **unlabeled** target domain
- Goal: achieving good performance on the target domain



Source Domain
with annotations

Target Domain
without annotations

Domain Adversarial Neural Networks



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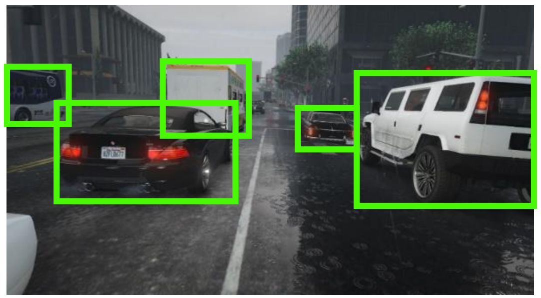
迁移学习用于计算机视觉

■ 物体检测



Synthetic images
with bounding-box annotations

Real-world images
with no annotations

Domain Adaptive Faster R-CNN for Object Detection in the Wild
Yuhua Chen, **Wen Li***, Christos Sakaridis, Dengxin Dai, and Luc Van Goo
IEEE International Conference on Computer Vision and Pattern Recognition(**CVPR**),2018.

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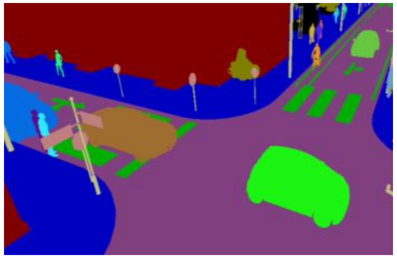
迁移学习用于计算机视觉

- 物体分割
  - 标注一张图片非常耗时（平均为1.5小时 [Cordts et al., 2016]）

Sample image from the Cityscapes dataset

迁移学习用于计算机视觉

■ 物体分割


Synthetic images
with pixel annotations

Real-world images
with no annotations

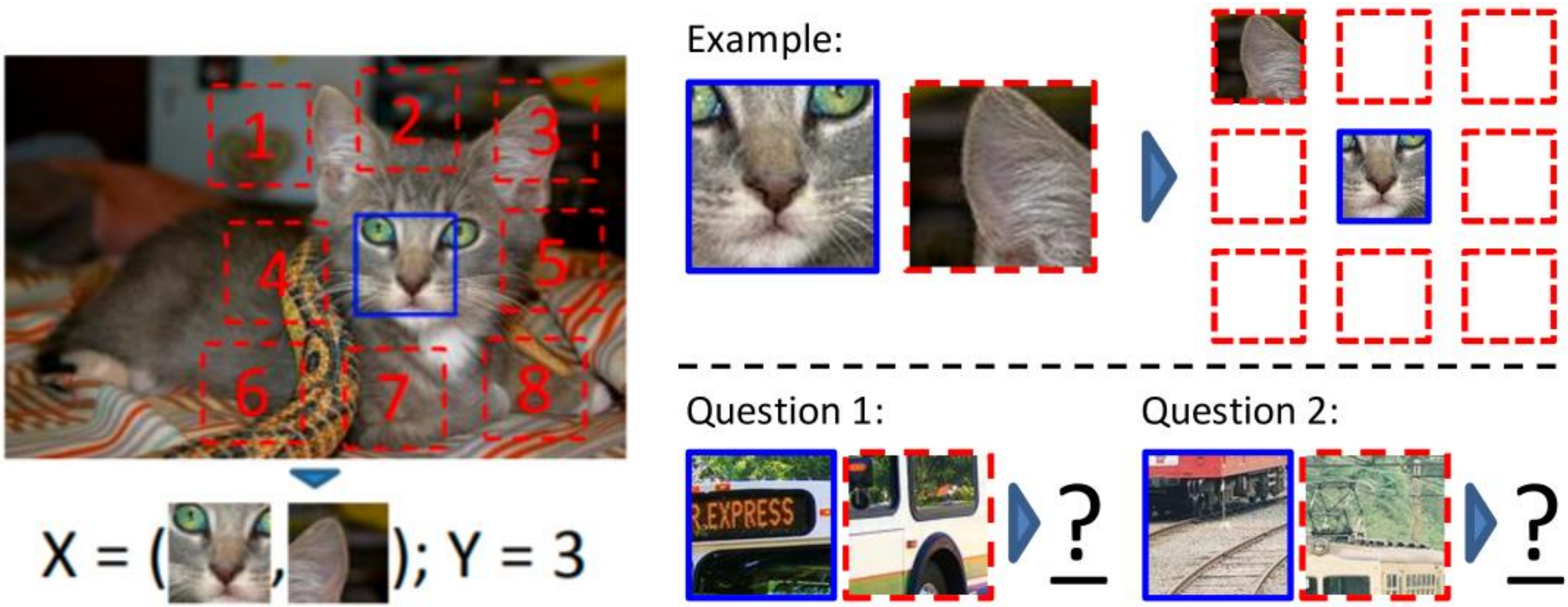
03 自监督学习及其他

自监督学习

- Self-Supervised Learning
  - 通过从数据中自动挖掘一些监督信息来训练神经网络

自监督学习

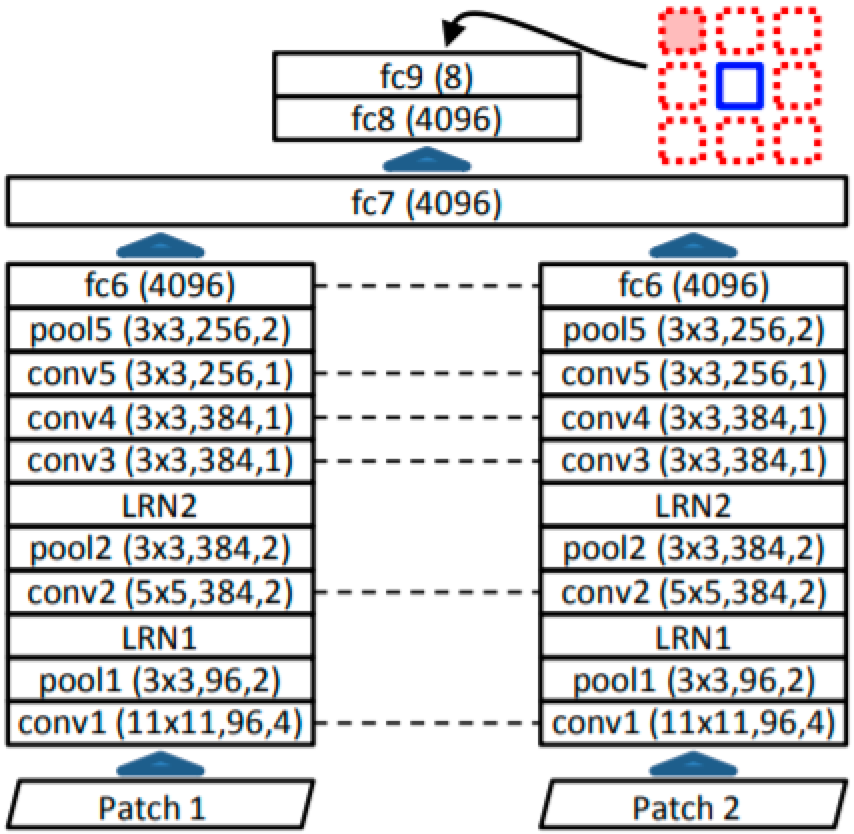
Self-Supervised Learning



C. Doersch, A. Gupta, and A. A. Efros. Unsupervised visual representation learning by context prediction. In Proceedings of International Conference on Computer Vision, 2015

自监督学习

■Self-Supervised Learning



	Lower Better		Higher Better		
	Mean	Median	11.25°	22.5°	30°
Scratch	38.6	26.5	33.1	46.8	52.5
Unsup. Tracking [57]	34.2	21.9	35.7	50.6	57.0
Ours	**33.2**	21.3	36.0	51.2	57.8
ImageNet Labels	33.3	**20.8**	**36.7**	**51.7**	**58.1**

Table 2. Accuracy on NYUv2.

C. Doersch, A. Gupta, and A. A. Efros. Unsupervised visual representation learning by context prediction. In Proceedings of International Conference on Computer Vision, 2015

自监督学习

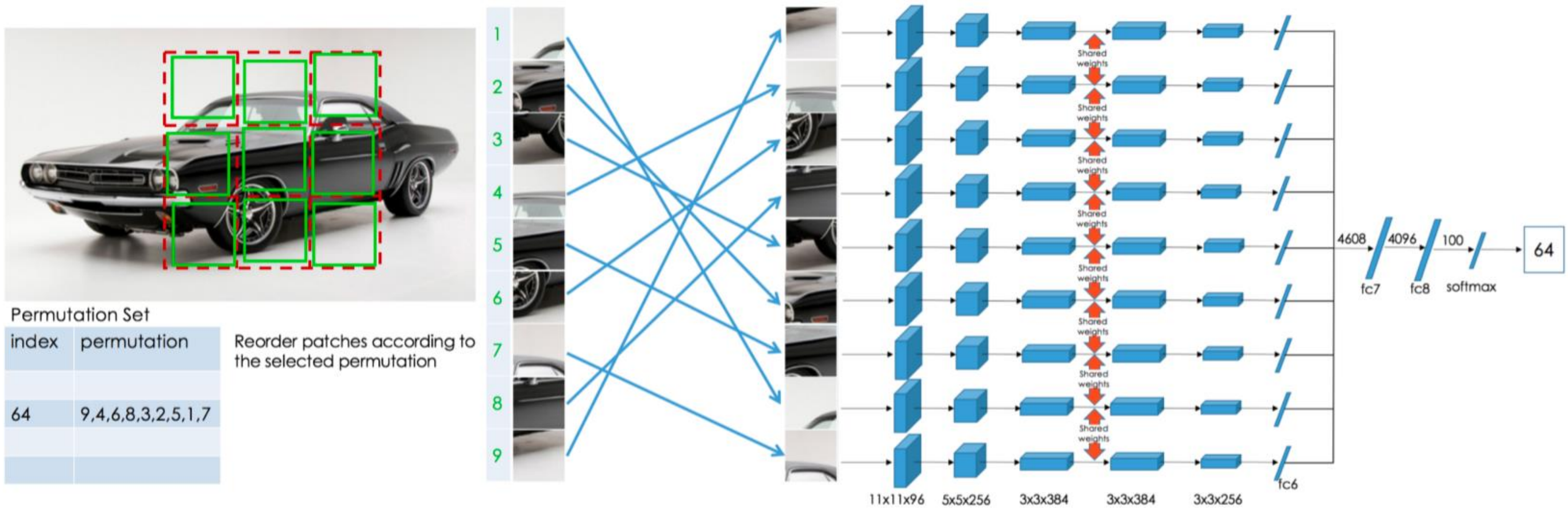
■ Self-Supervised Learning

(a) (b) (c)

M. Noroozi, and P. Favaro. Unsupervised Learning of Visual Representations by Solving Jigsaw Puzzles. In European Conference on Computer Vision, 2016.

自监督学习

■Self-Supervised Learning



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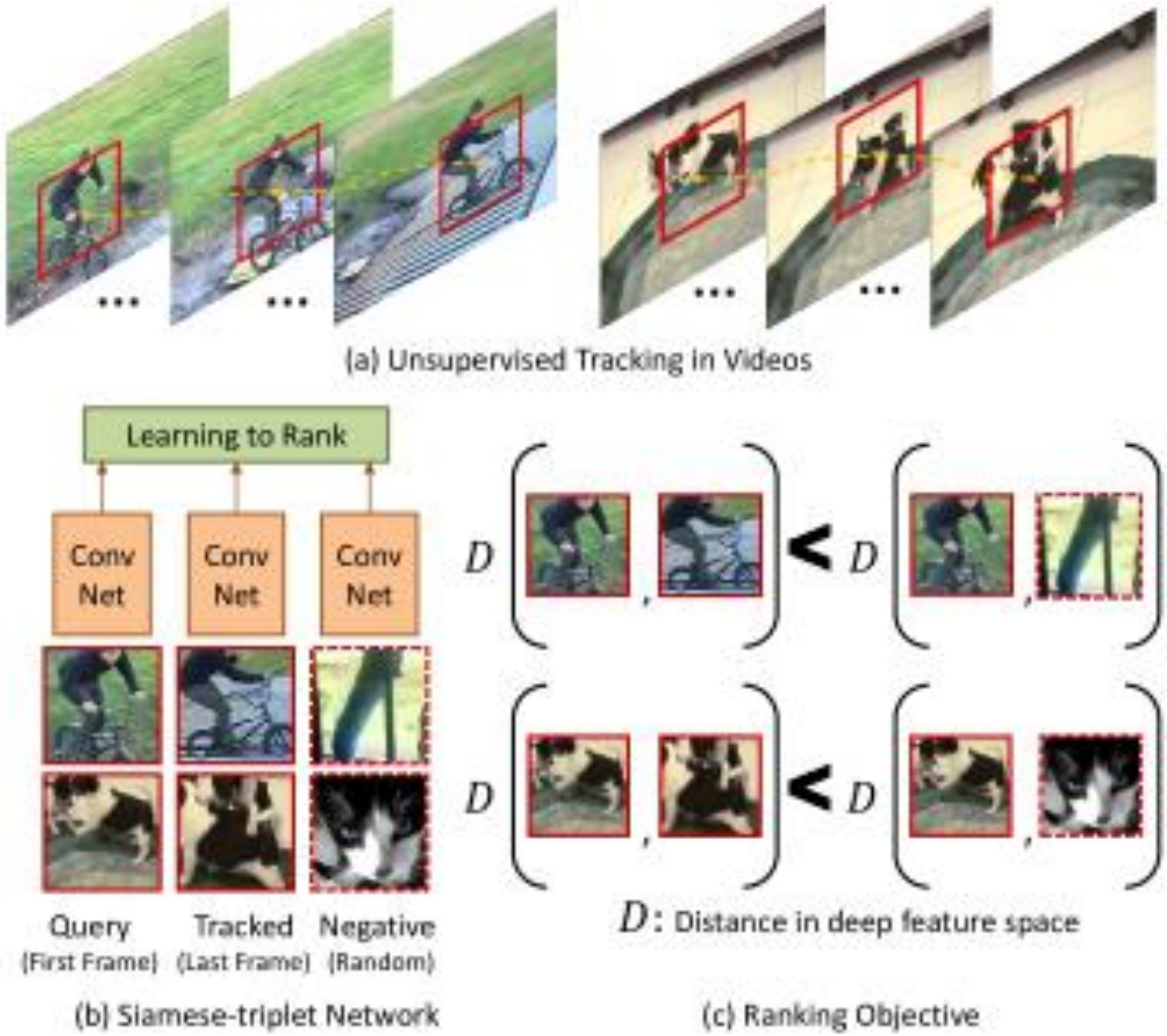
自监督学习



X. Wang, and A. Gupta. Unsupervised learning of visual representations using videos. In Proceedings of International Conference on Computer Vision, 2015

自监督学习

■Self-Supervised Learning

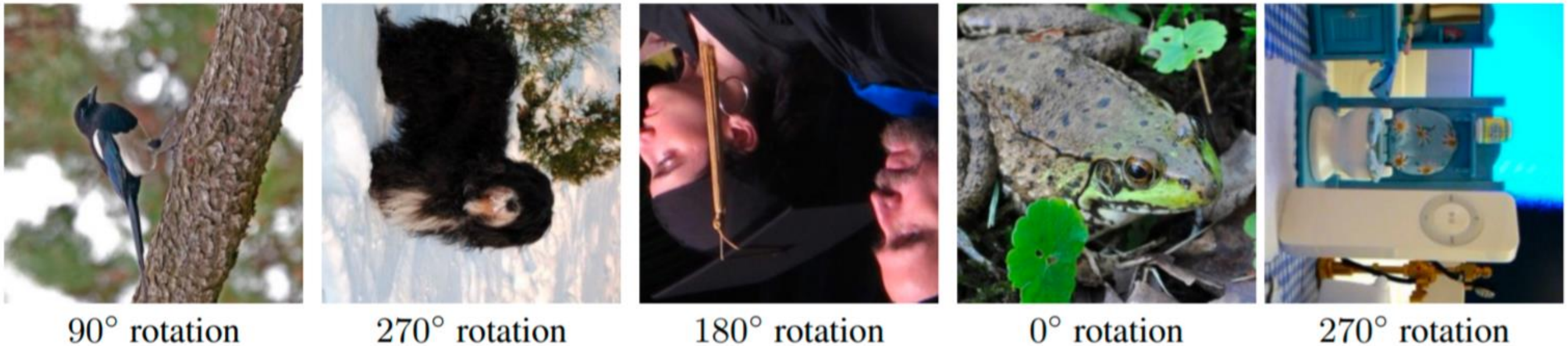
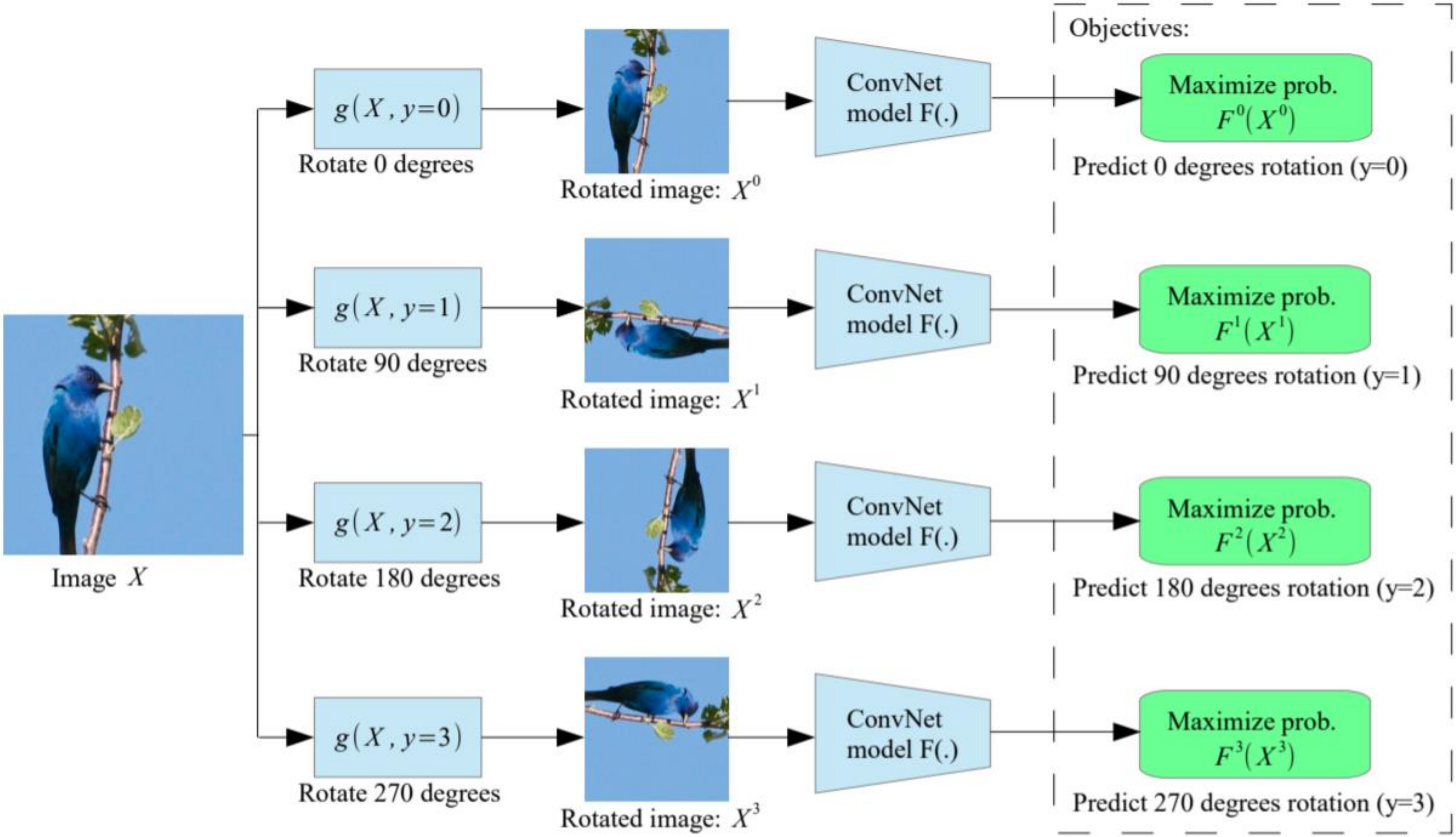


Figure 1: Images rotated by random multiples of 90 degrees (e.g., 0, 90, 180, or 270 degrees). The core intuition of our self-supervised feature learning approach is that if someone is not aware of the concepts of the objects depicted in the images, he cannot recognize the rotation that was applied to them.

S. Gidaris, P. Singh, and N. Komodakis. Unsupervised representation learning by predicting image rotations. In International Conference on Learning Representations (ICLR), 2018

自监督学习



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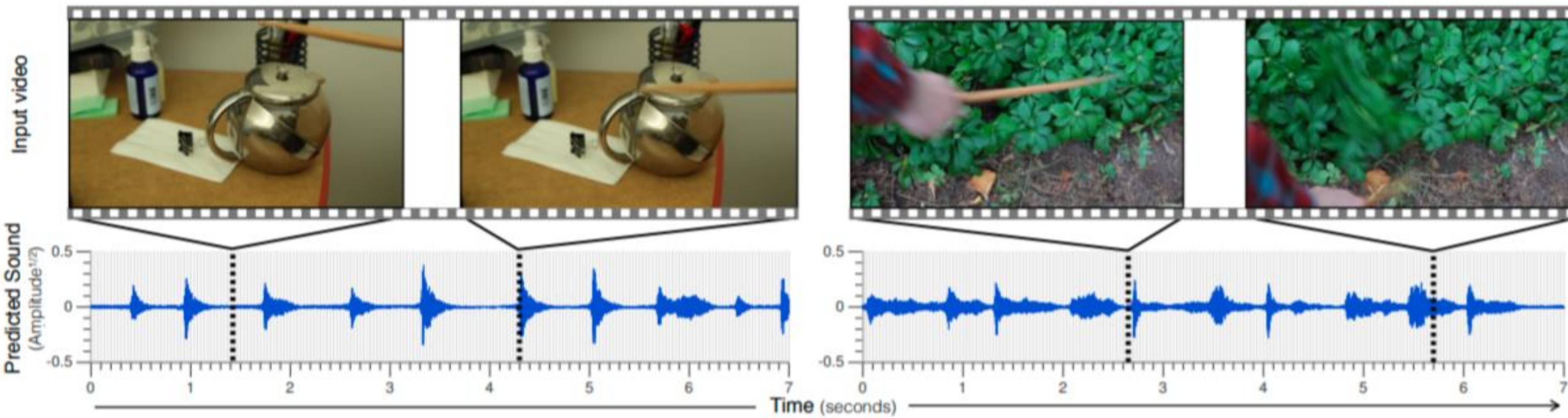
声音作为监督



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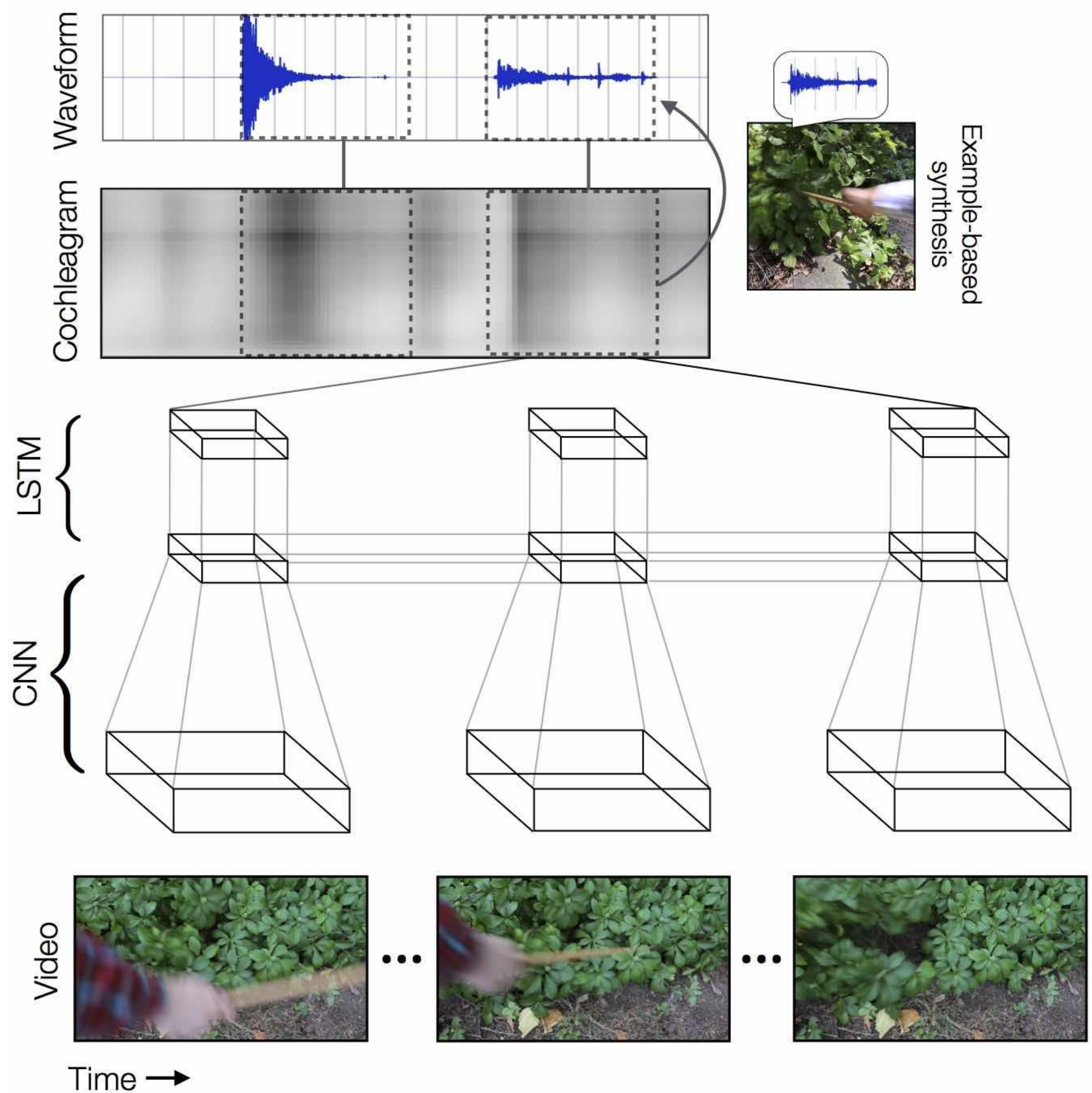

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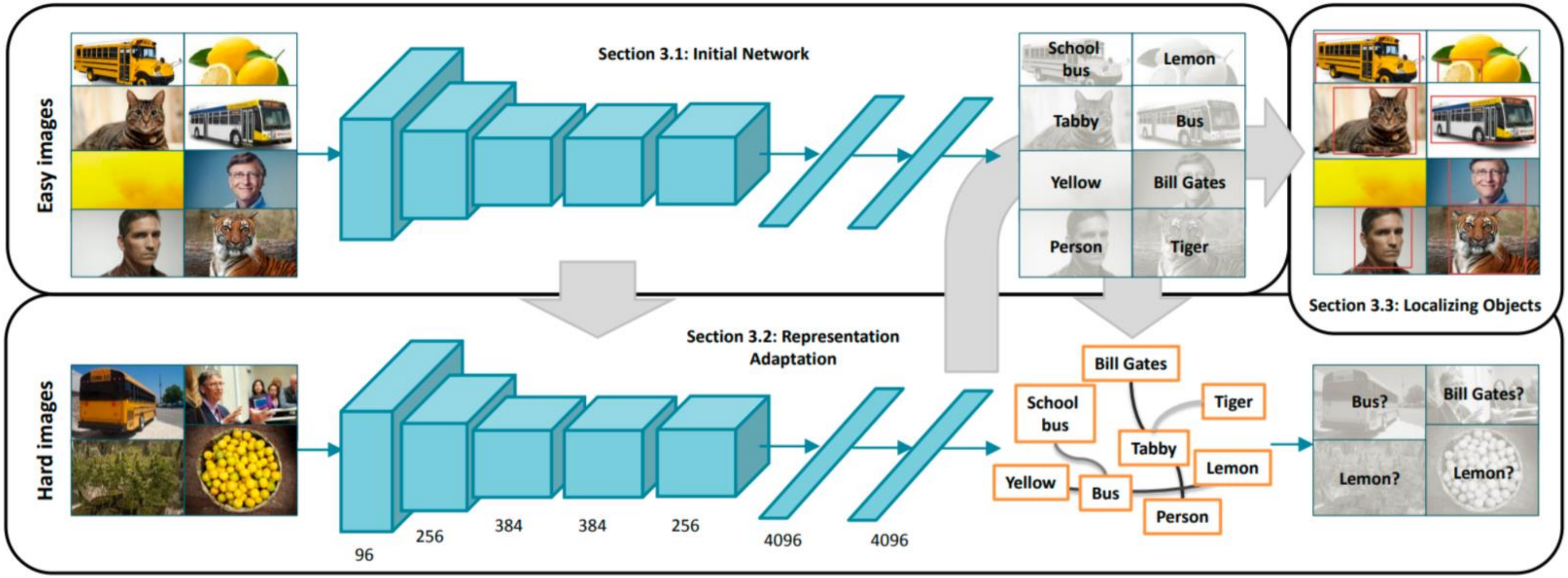
声音作为监督


Visually Indicated Sounds
Andrew Owens
Phillip Isola
Josh McDermott
Antonio Torralba
Edward Adelson
William Freeman

从网络数据学习

- Webly Supervised Learning



https://arxiv.org/pdf/1505.01554.pdf

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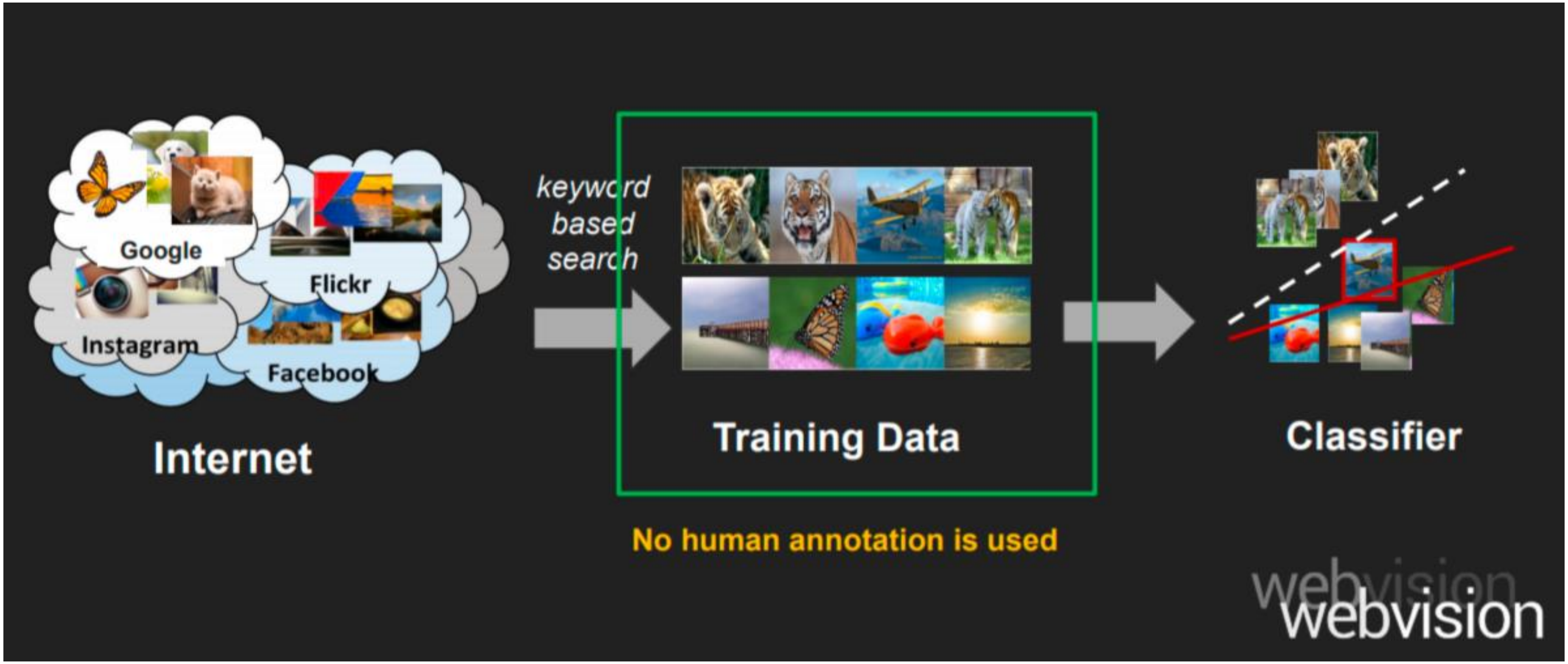
从网络数据学习

- Webly Supervised Learning



https://data.vision.ee.ethz.ch/cvl/webvision//workshop.html

从网络数据学习

■Webly Supervised Learning

WebVision 2.0 dataset

- 5,000 categories
- 16M internet images
- 290K validation images
- 290K test images

WebVision Challenge

- WebVision Image Classification Track

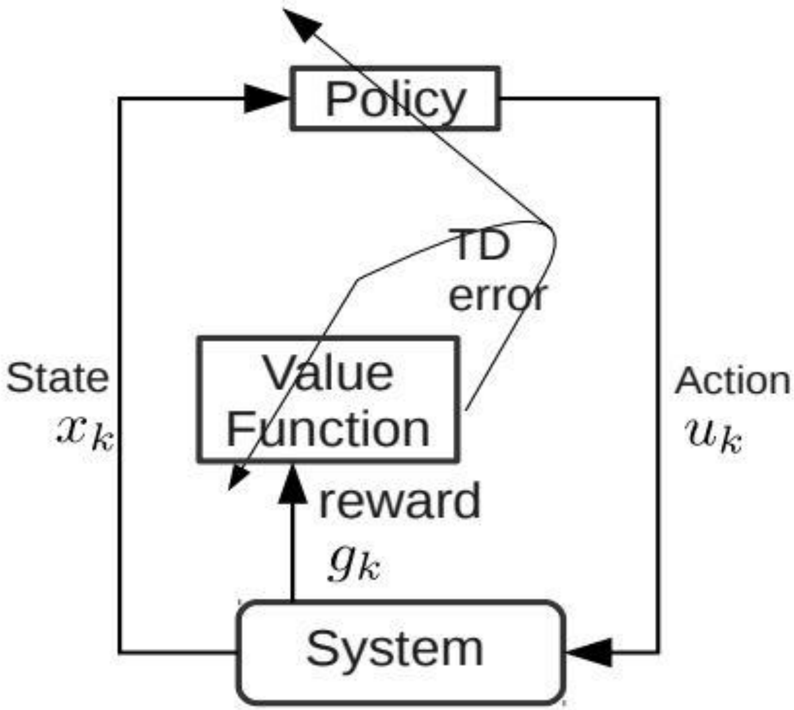
https://data.vision.ee.ethz.ch/cvl/webvision//workshop.html

04 AlphaGo算法

强化学习

■数据不是静态的，是从动态环境中获得

■结果只有在一系列动作完成后才知道，在执行过程中，是没有确切的supervision的



•状态空间（state space）：对于围棋来说，每一个棋盘布局（记为s）就是一个状态。所有可能的棋盘布局就是状态空间。

•动作空间 （action space）：对于围棋来说，所有可能落子的位置就是一个动作空间

•状态转化：你落子之后，对手可能会下的子。如果是两台alpha zero互搏的话，相互是对方环境的一个部分。

•奖励函数：你落子之后得到的信号。在围棋里面，就是胜率的一个正函数。胜率越大，奖赏越大。

An introduction to reinforcement learning

深度理解AlphaGo

- 见另一slides

04 其他

Neural Architecture Search

- 设计神经网络是另一个Hand-Crafted
  - 在一定空间内自动搜索神经网络的结构

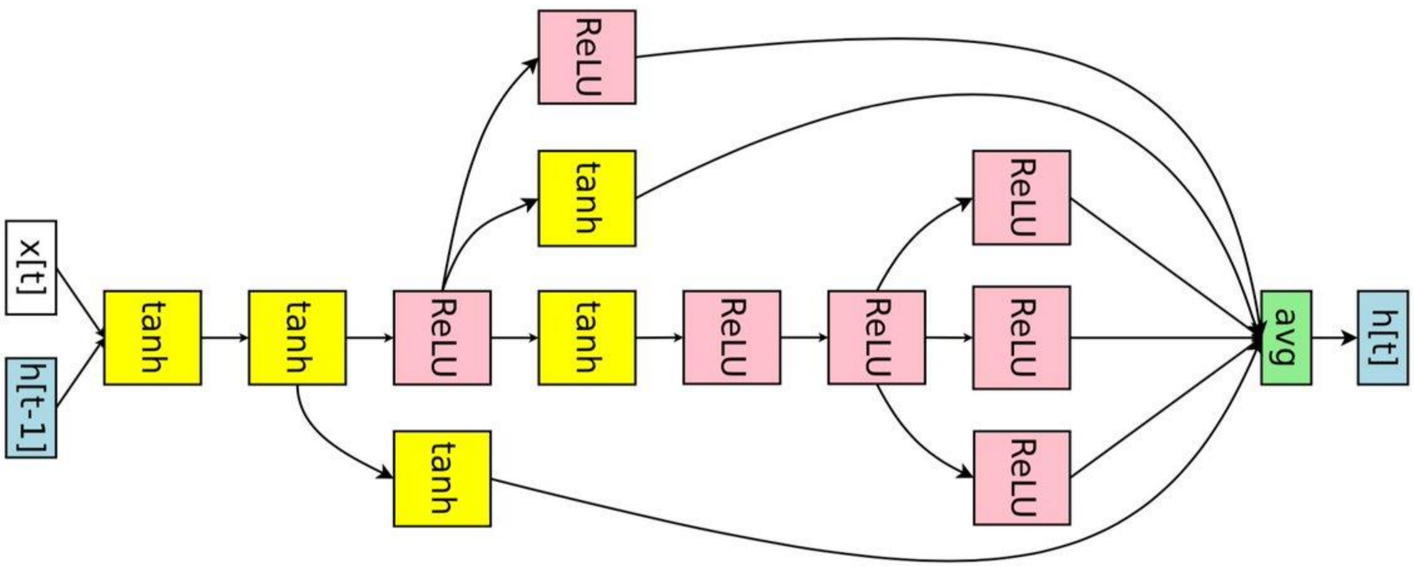


Figure 6. The RNN cell ENAS discovered for Penn Treebank.

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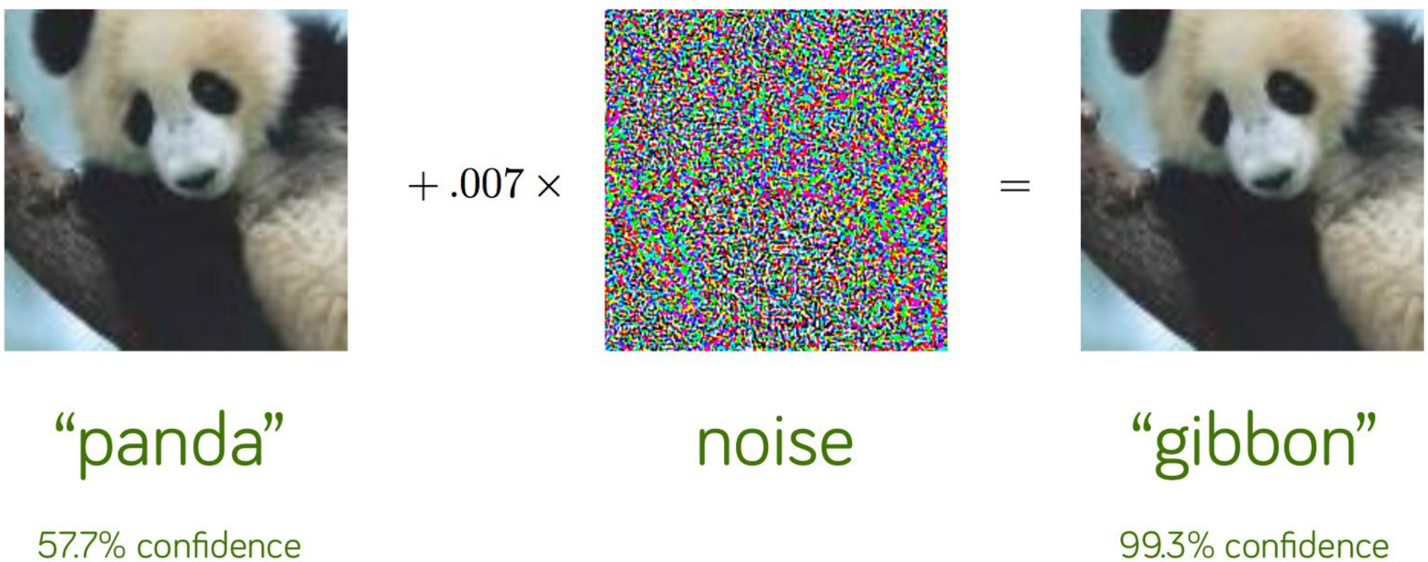
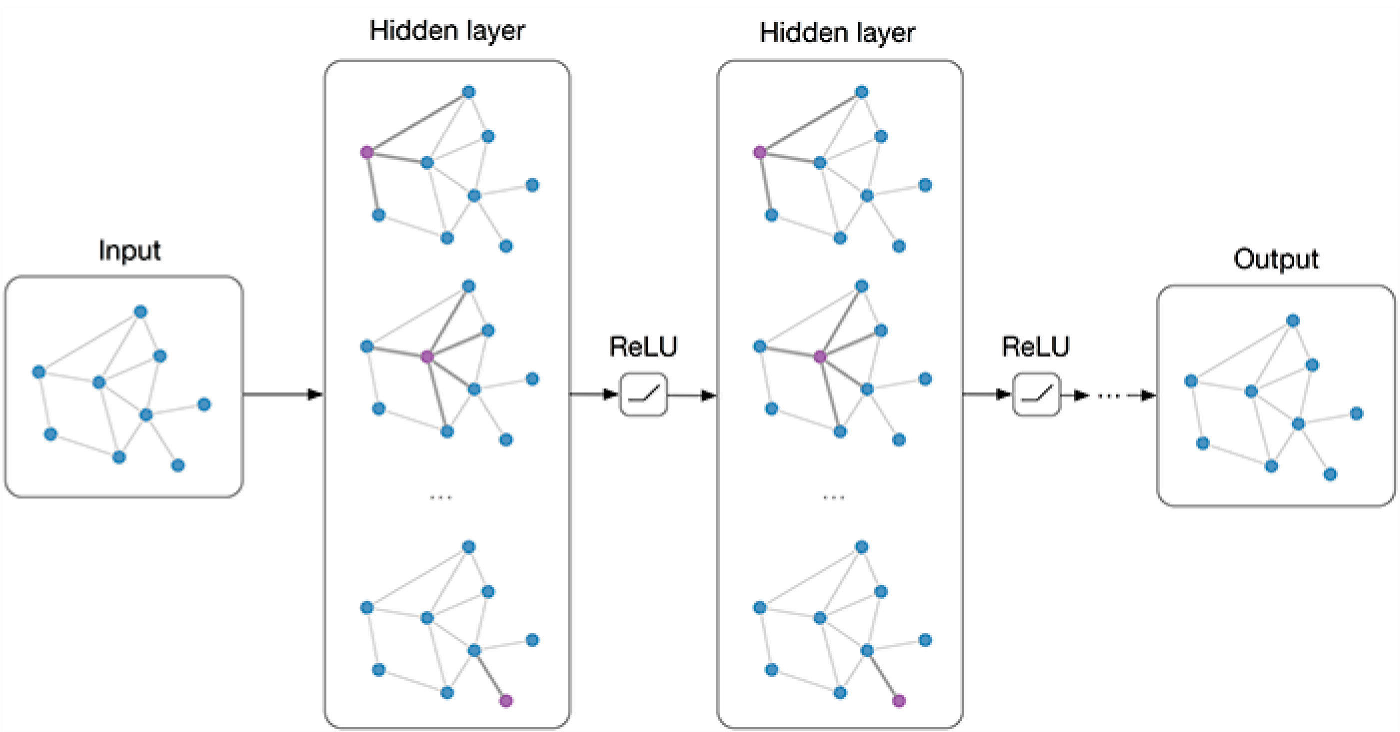
Adversarial Examples

- 神经网络的分界面复杂，且存在“空洞”



图神经网络

- 是对传统卷积神经网络的拓展
  - 传统的卷积神经网络看作是特殊的图，grid



考核方式

- 平时成绩：40%（slides报告）
- 期末成绩：60%（实验报告）
- 形式
  - 组队：两人一组（最后一次课做presentation）
  - 用课程中讲述的内容做一个自己感兴趣的应用
  - 报告内容：背景介绍、背景介绍、已有算法总结、报告中采用的算法描述、实验结果、结论。不少于10页。
  - 加分项：基于现有的算法，提出自己新的想法，使得原算法得到改进
  - 截止时间：2020年4月22日
  - 严禁抄袭

发送到我邮箱liwen@uestc.edu.cn
邮件题目 “人工智能导论报告_姓名+姓名”

Thank You!

谢谢大家！

liwen@uestc.edu.cn