

Introduction to Statistical Learning and Machine Learning

Chap 7 -
Neural
Network(Cont.)

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Applications by deep learning



人工智能领域的两股主流

基于统计学习的方法

基于神经网络的方法



在语音识别上的应用

| 音素 (Phoneme) 识别

2009年, Deep belief networks for phone recognition一文中, 深度学习的错误率: 23.0%

与之比较, 不同GMM方法相应错误率:

- Maximum Likelihood Training (MLT): 25.6%,
- Sequence-Discriminative Training (SDT): 21.7%

| 单词 (Word) 识别

2011年, Context-Dependent Pre-Trained Deep Neural Networks for Large-Vocabulary Speech Recognition一文中, 深度学习的错误率: 30.4%

与之比较, 不同GMM方法相应错误率:

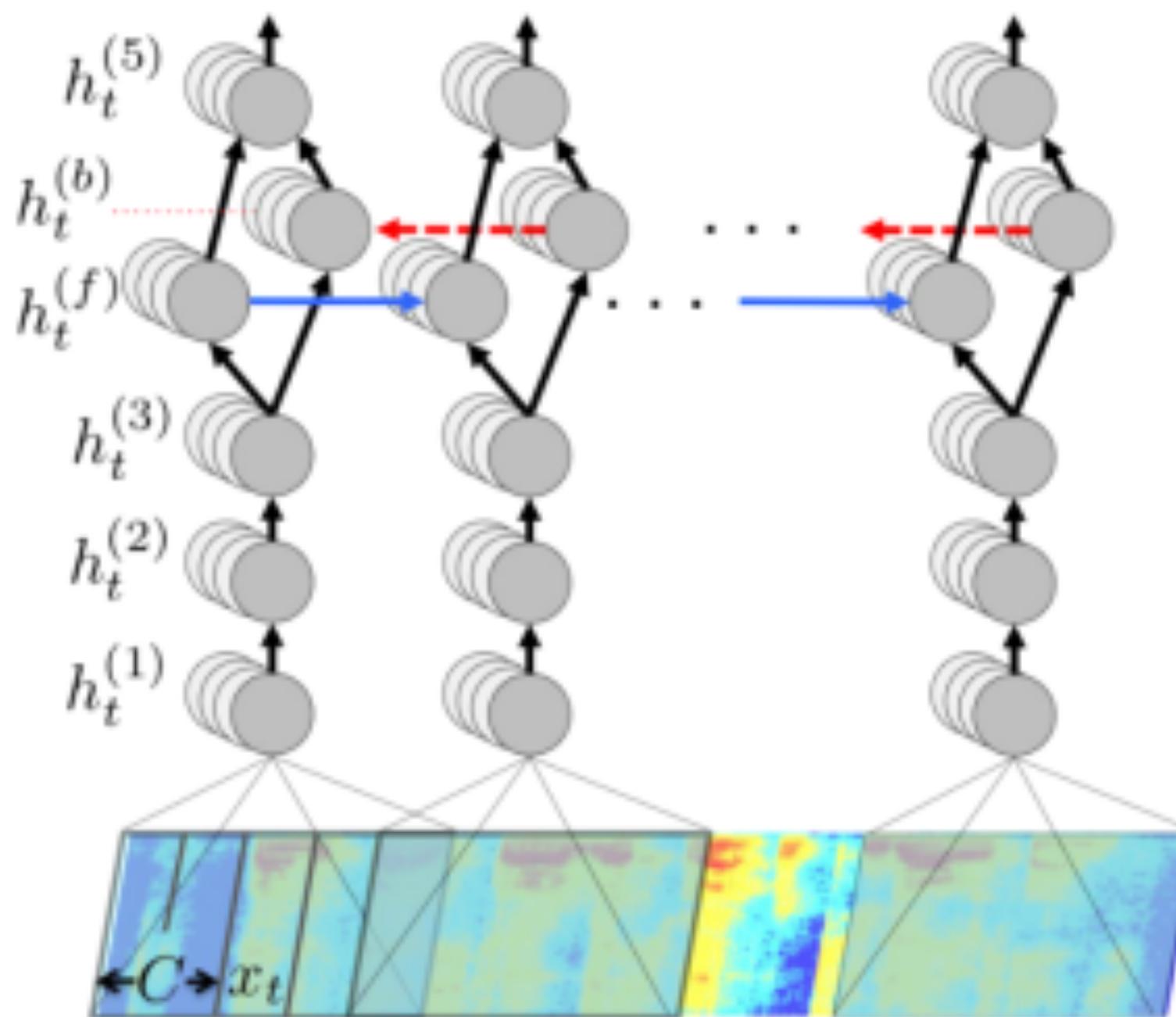
- Maximum Likelihood Training (MLT): 39.6%,
- Sequence-Discriminative Training (SDT): 36.2%

在语音识别上的应用

对话识别

2011年基于深度学习取得了十年来的重大突破

2014年百度推出基于RNN的DeepSpeech
在7380小时语音上叠加不同背景噪音生成10万小时级数据



Dataset	Type	Hours	Speakers
WSJ	read	80	280
Switchboard	conversational	300	4000
Fisher	conversational	2000	23000
Baidu	read	5000	9600

Model	SWB	CH	Full
Vesely et al. (GMM-HMM BMMI) [43]	18.6	33.0	25.8
Vesely et al. (DNN-HMM sMBR) [43]	12.6	24.1	18.4
Maas et al. (DNN-HMM SWB) [28]	14.6	26.3	20.5
Maas et al. (DNN-HMM FSH) [28]	16.0	23.7	19.9
Seide et al. (CD-DNN) [39]	16.1	n/a	n/a
Kingsbury et al. (DNN-HMM sMBR HF) [22]	13.3	n/a	n/a
Sainath et al. (CNN-HMM) [36]	11.5	n/a	n/a
DeepSpeech SWB	20.0	31.8	25.9
DeepSpeech SWB + FSH	13.1	19.9	16.5

在图像识别上的应用

IMAGENET 大规模视觉识别挑战赛 (ILSVRC 2014)

物体识别项目，15M图片，22K类

名称	时间	Top-5 Error
AlexNet	2012年	15.3%
OverFeat (New York University)	2013年	13.8%
VGG Net (Oxford)	2014年	7.3%
GoogLeNet (Google)	2014年	6.6%
人类	/	5.1%
Microsoft	2015年2月6日	4.94%
Google	2015年2月11日	4.82%
Microsoft	2015年12月10日	3.57%
Google	2015年12月11日	3.58%
Google	2016年2月23日	3.08%

在图像识别上的应用

人脸识别

LFW (5749个人, 13233张人脸照片)

名称	时间	Top-1 Accuracy
传统方法	/	~96%
DeepFace (Facebook)	2014年	97.35%
人类	/	97.53%
GaussianFace (香港中文大学)	2014年	98.52%
DeepID3 (香港中文大学)	2015年2月	99.53%
Facenet (Google)	2015年6月	99.63%
腾讯优图	2015年10月	99.65%
百度IDL	2015年10月	99.77%

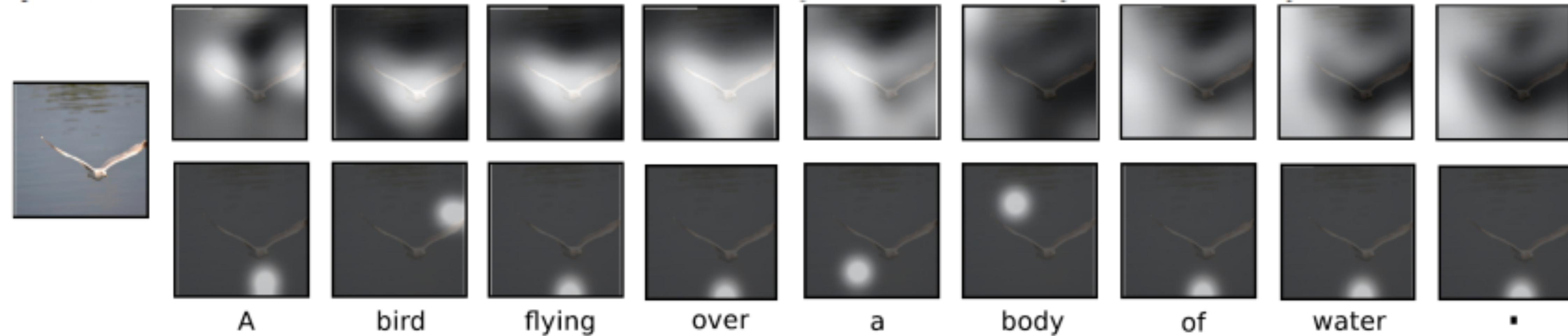
Youtube Face DB (8M个人, 200M张人脸照片)

FaceNet (Google) 识别率可达95.12% (2015年)

在图像识别上的应用

| 关注度 (Attention)

Yoshua Bengio团队, 2016年



A little girl sitting on a bed with a teddy bear.

A group of people sitting on a boat in the water.

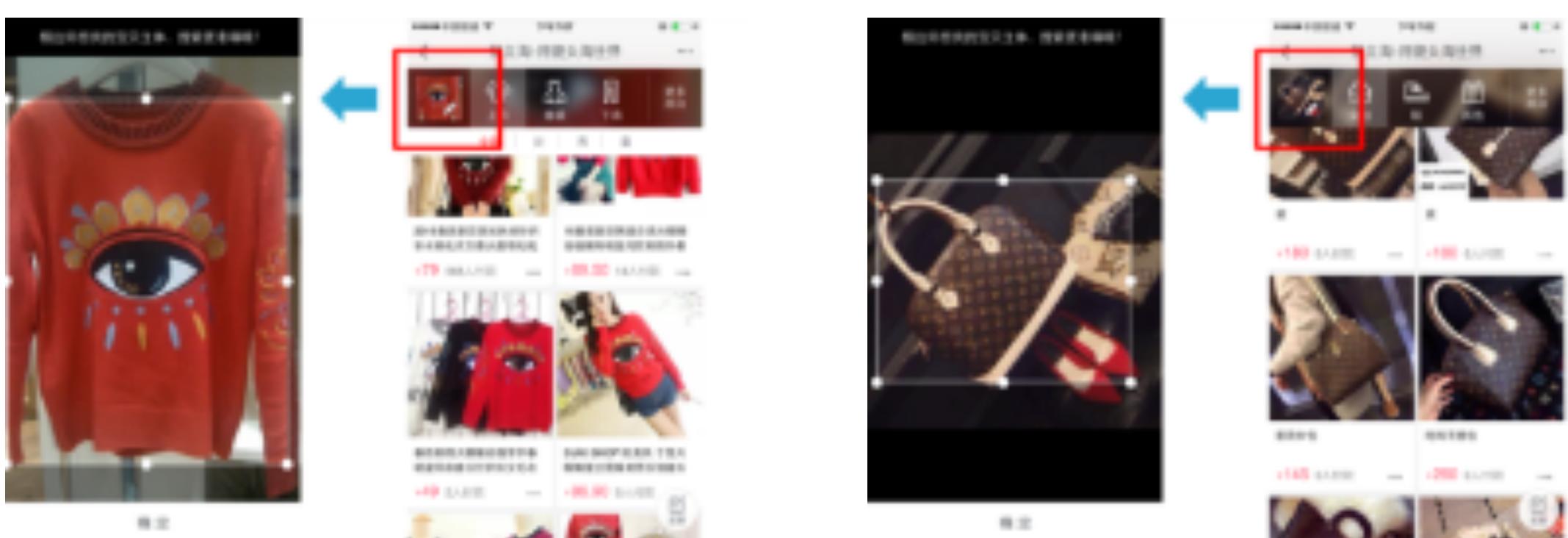
A giraffe standing in a forest with trees in the background.

A woman is throwing a frisbee in a park.

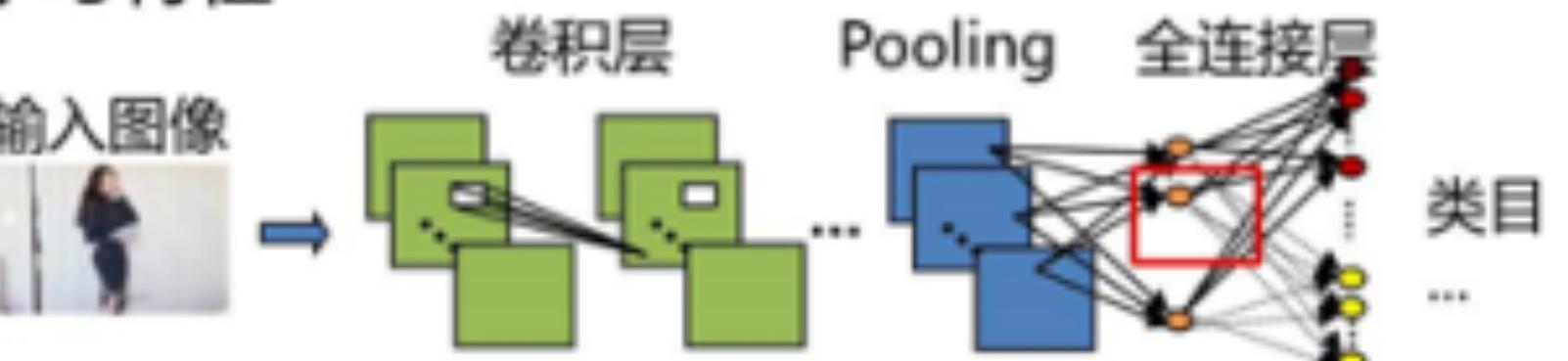
在图像识别上的应用

| 海量图像的分类、识别

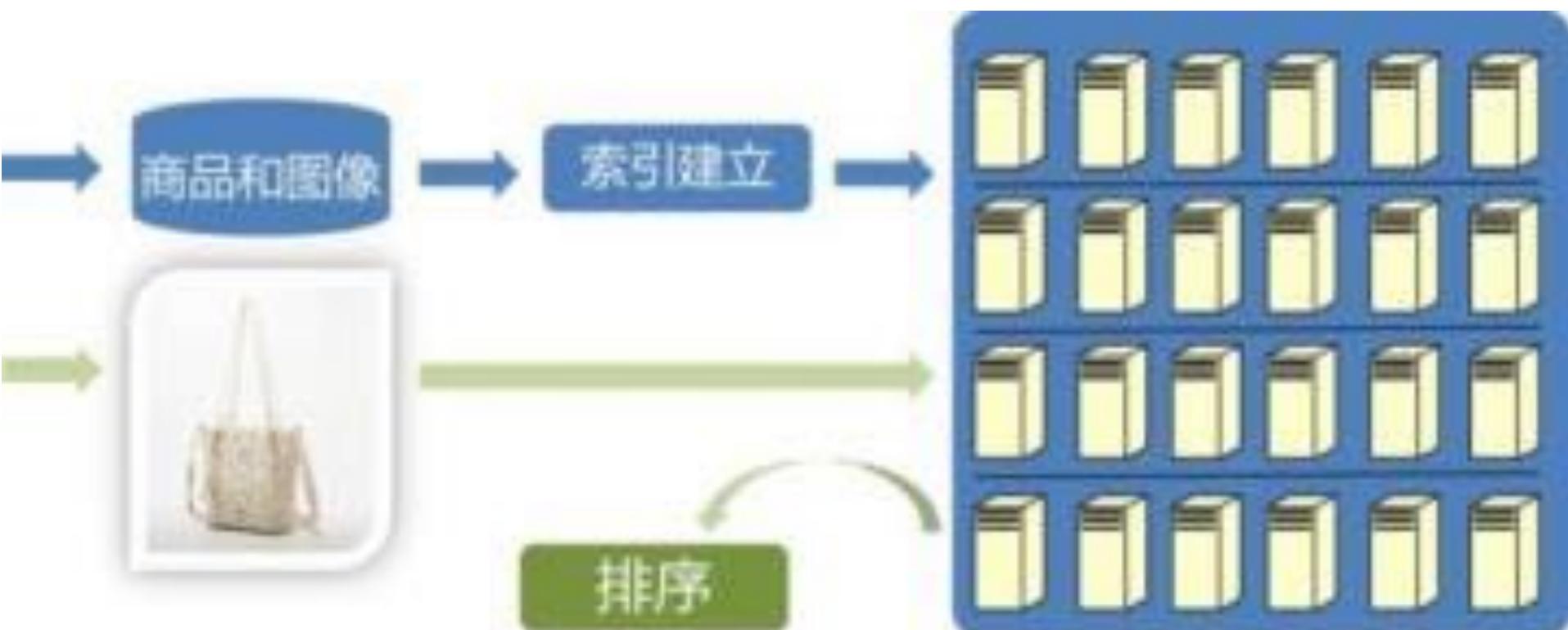
拍立淘



深度学习特征



局部特征



在图像识别上的应用

图像描述

Junhua Mao等人, 2016



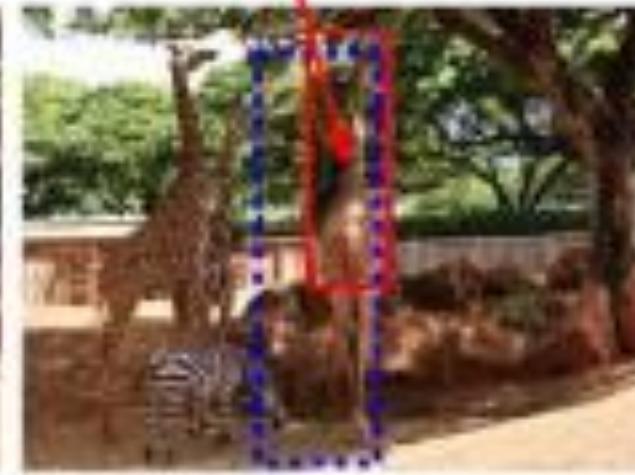
The giraffe behind the zebra that is looking up.



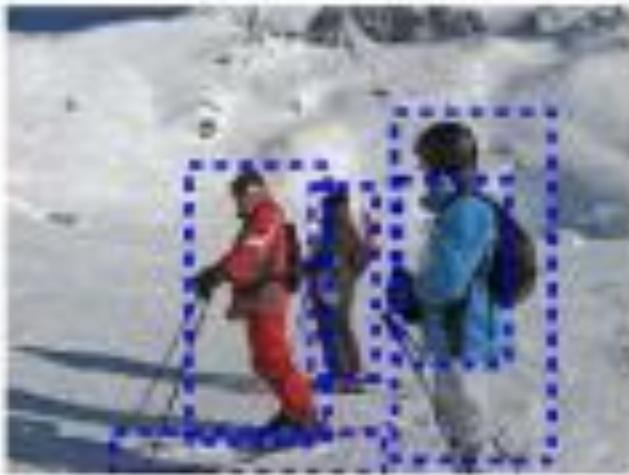
The giraffe with its back to the camera.



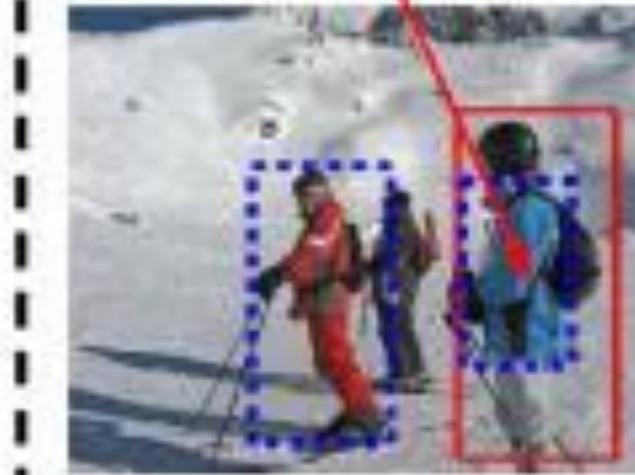
The giraffe on the right.



A zebra.



A skier with a black helmet, light blue and black jacket, backpack, and light grey pants standing.



The man in black.



The man in red.



The skis.



Guy with dark short hair in a white shirt.



A woman with curly hair playing Wii.



*The woman in white.



The controller in the woman's hand.

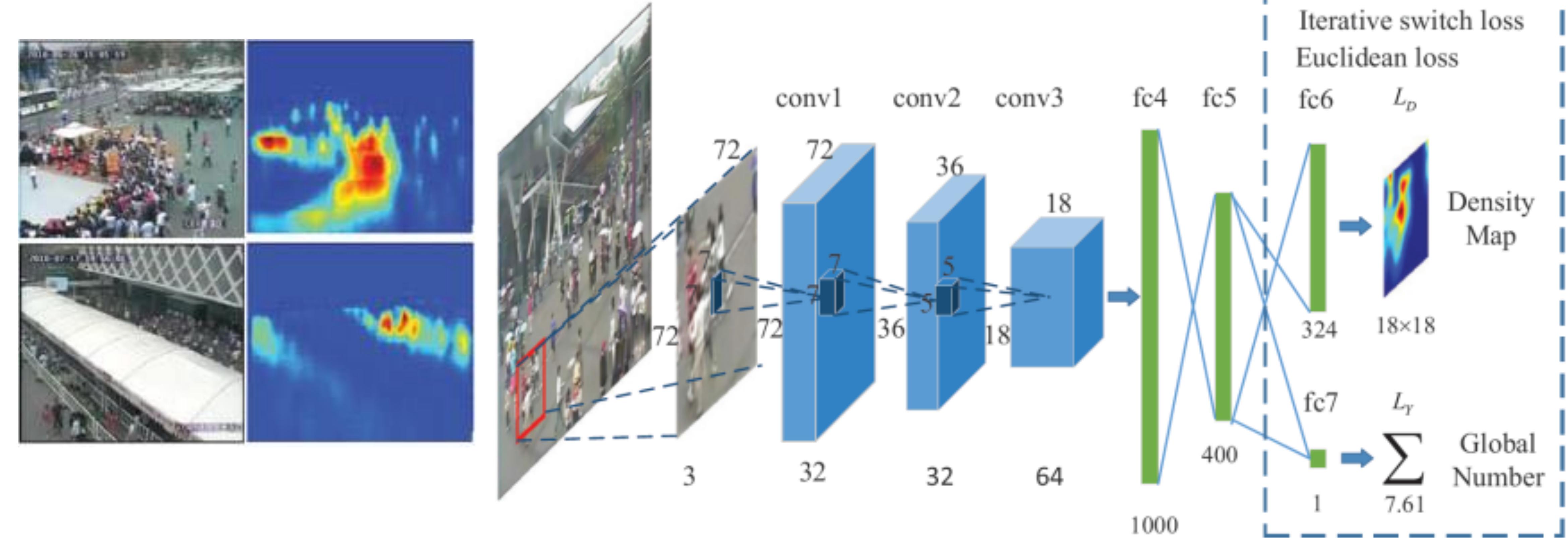


在图像识别上的应用

人群计数

Cong Zhang等人, 2016

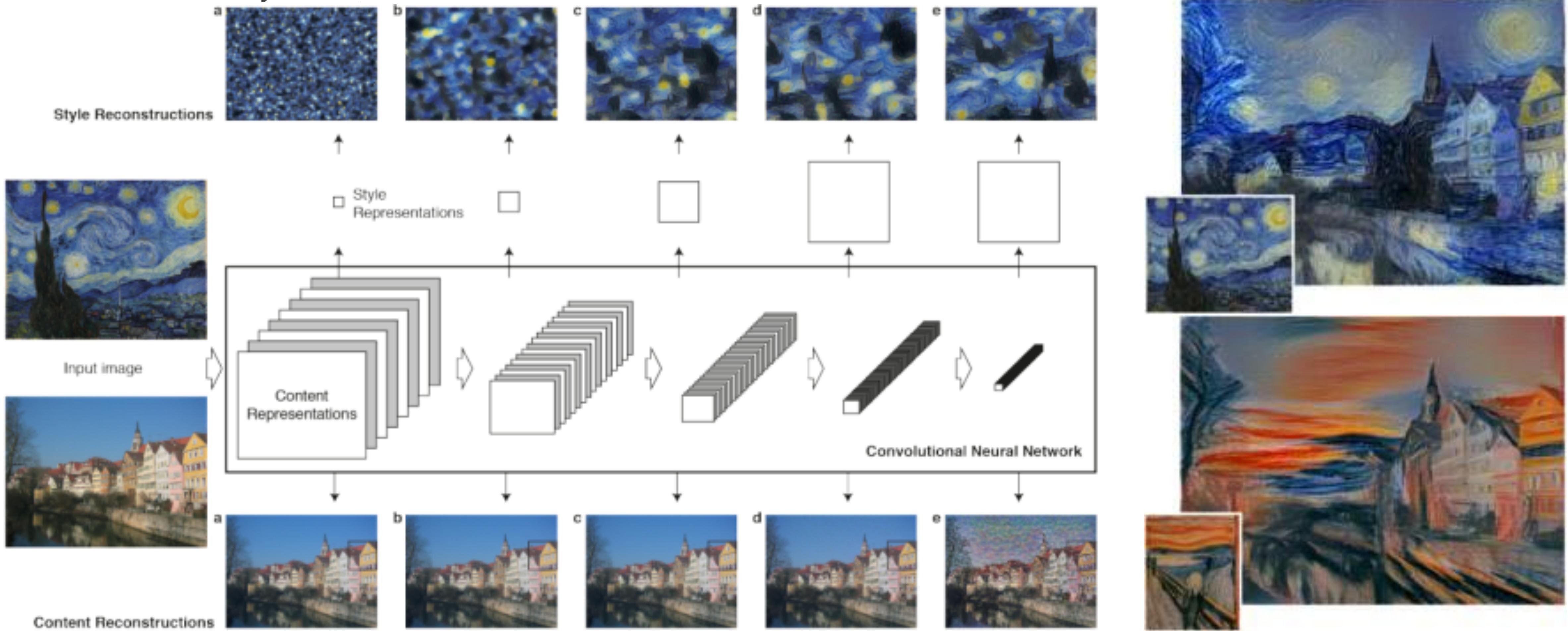
Method	Scene 1	Scene 2	Scene 3	Scene 4	Scene 5	Average
LBP+RR	13.6	58.9	37.1	21.8	23.4	31.0
Crowd CNN	10.0	15.4	15.3	25.6	4.1	14.1
Fine-tuned Crowd CNN	9.8	14.1	14.3	22.2	3.7	12.9
Luca Fiaschi et al. [7]	2.2	87.3	22.2	16.4	5.4	26.7
Ke et al. [6]	2.1	55.9	9.6	11.3	3.4	16.5
Crowd CNN+RR	2.0	29.5	9.7	9.3	3.1	10.7



在图像处理上的应用

绘画风格变换

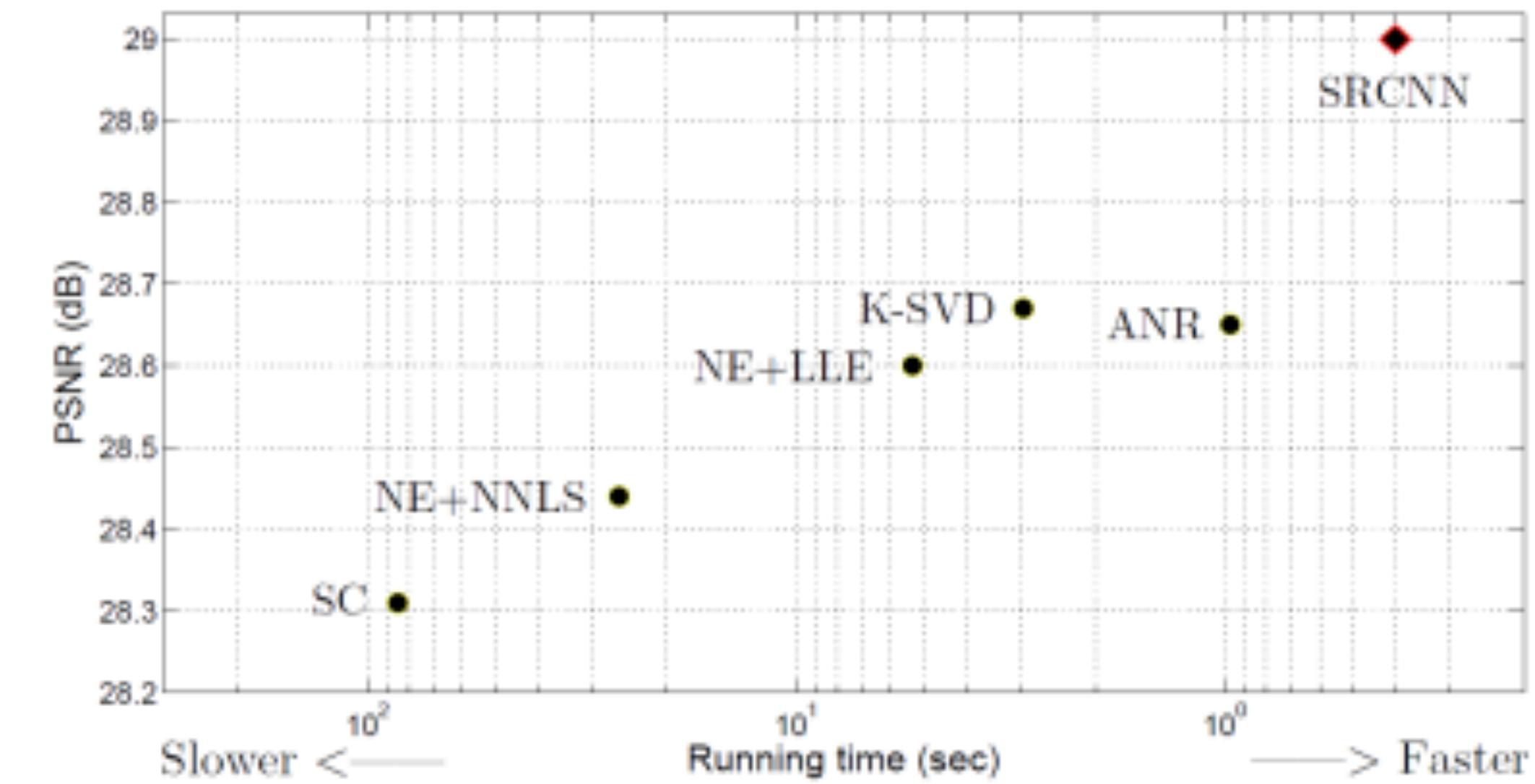
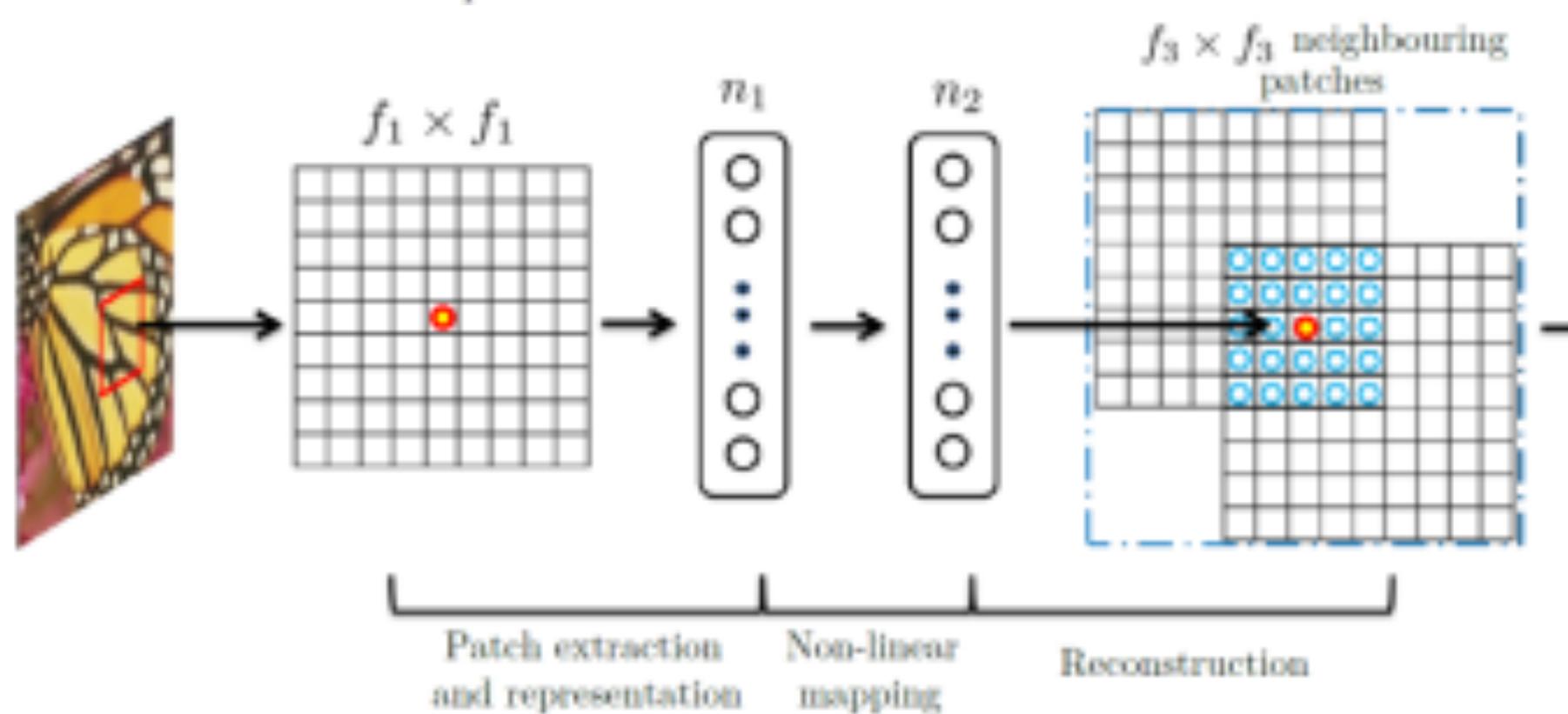
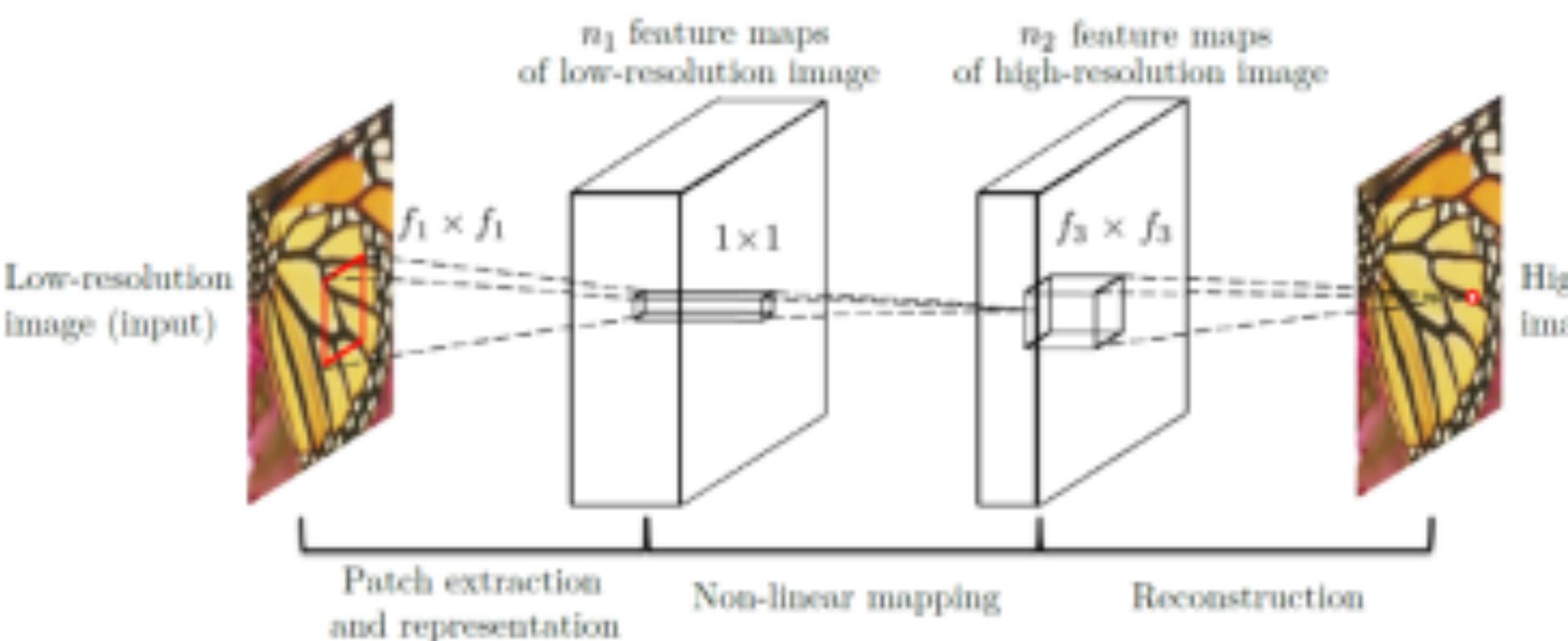
Leon A. Gatys等人, 2015



在图像处理上的应用

| 超分辨率

2014年Xiaou Tang等人的工作
信噪比高、速度快



在自然语言理解上的应用

Word2Vec的适时出现

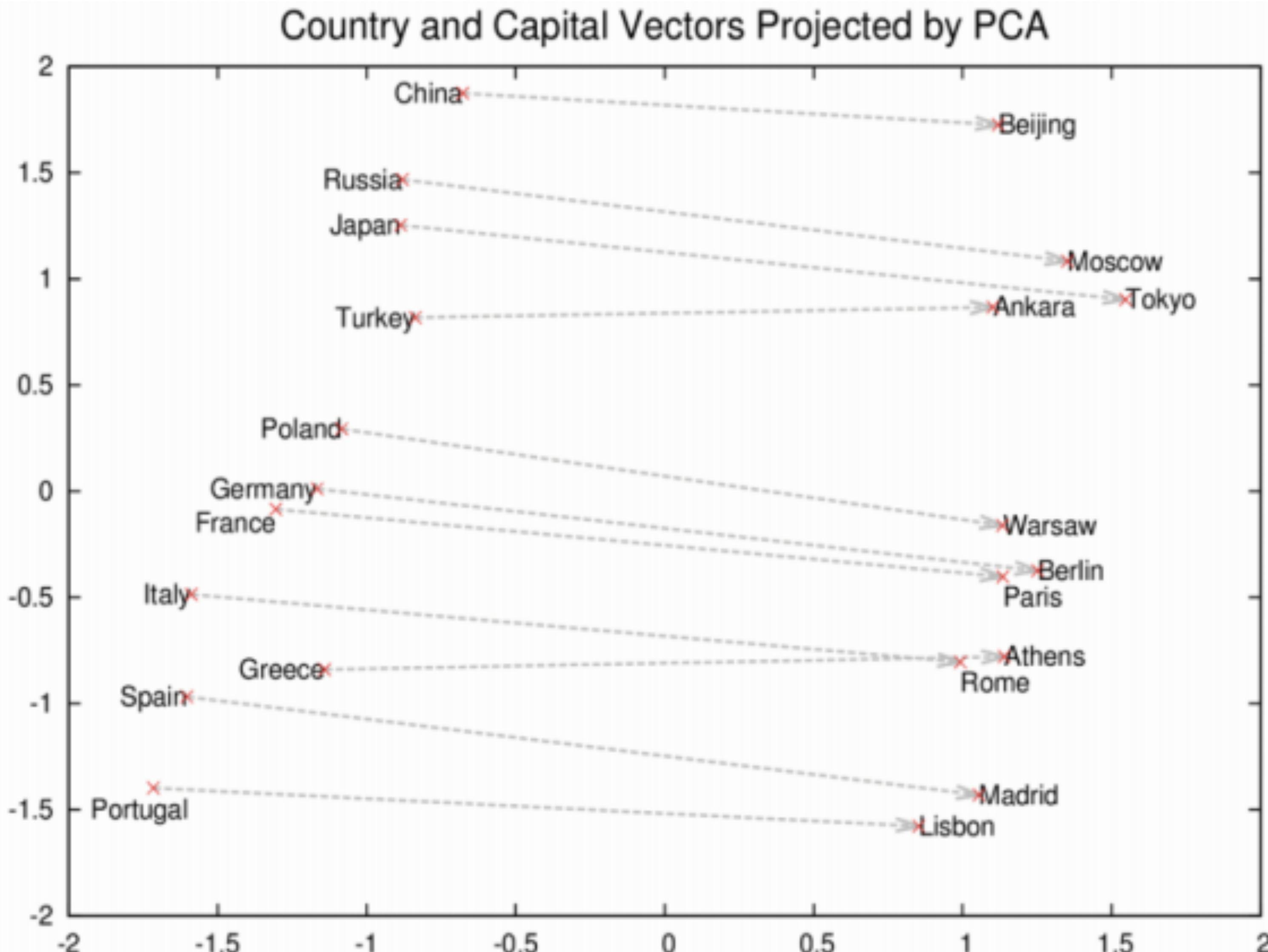
词语获得了更稠密的向量表示

词语的相关性更容易计算（余弦距离）

深度学习具备了重要的输入

输入：计算机

	输入：计算机
自动化	0.674172
应用	0.614087
自动化系	0.611133
材料科学	0.607891
集成电路	0.600370
技术	0.597519
电子学	0.591316
建模	0.577239
工程学	0.572856
微电子	0.570087



在自然语言理解上的应用

| 定制化的NLP应用

将过去统计机器翻译的成熟成果迁移到神经网络模型上
基于深度学习的情感分析
利用神经网络模型检测小说中的人物关系

| 从文本理解到文本生成

新闻、专利、百科词条、论文的生成
智能人机对话系统

| 大规模知识图谱的构建与应用

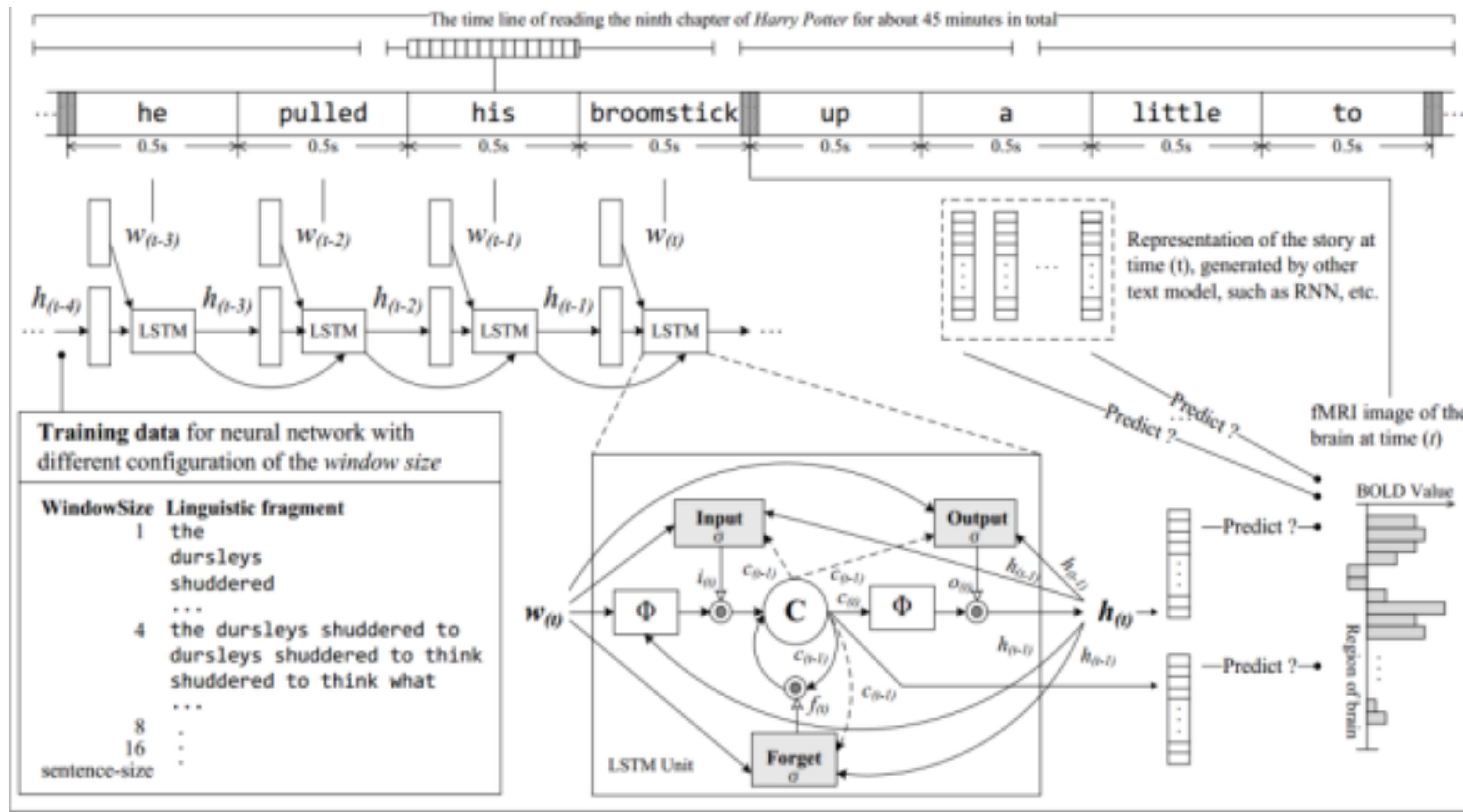
阅读理解、机器翻译、文档摘要
新概念、新知识的自动学习
基于知识图谱实现智能推理

在自然语言理解上的应用

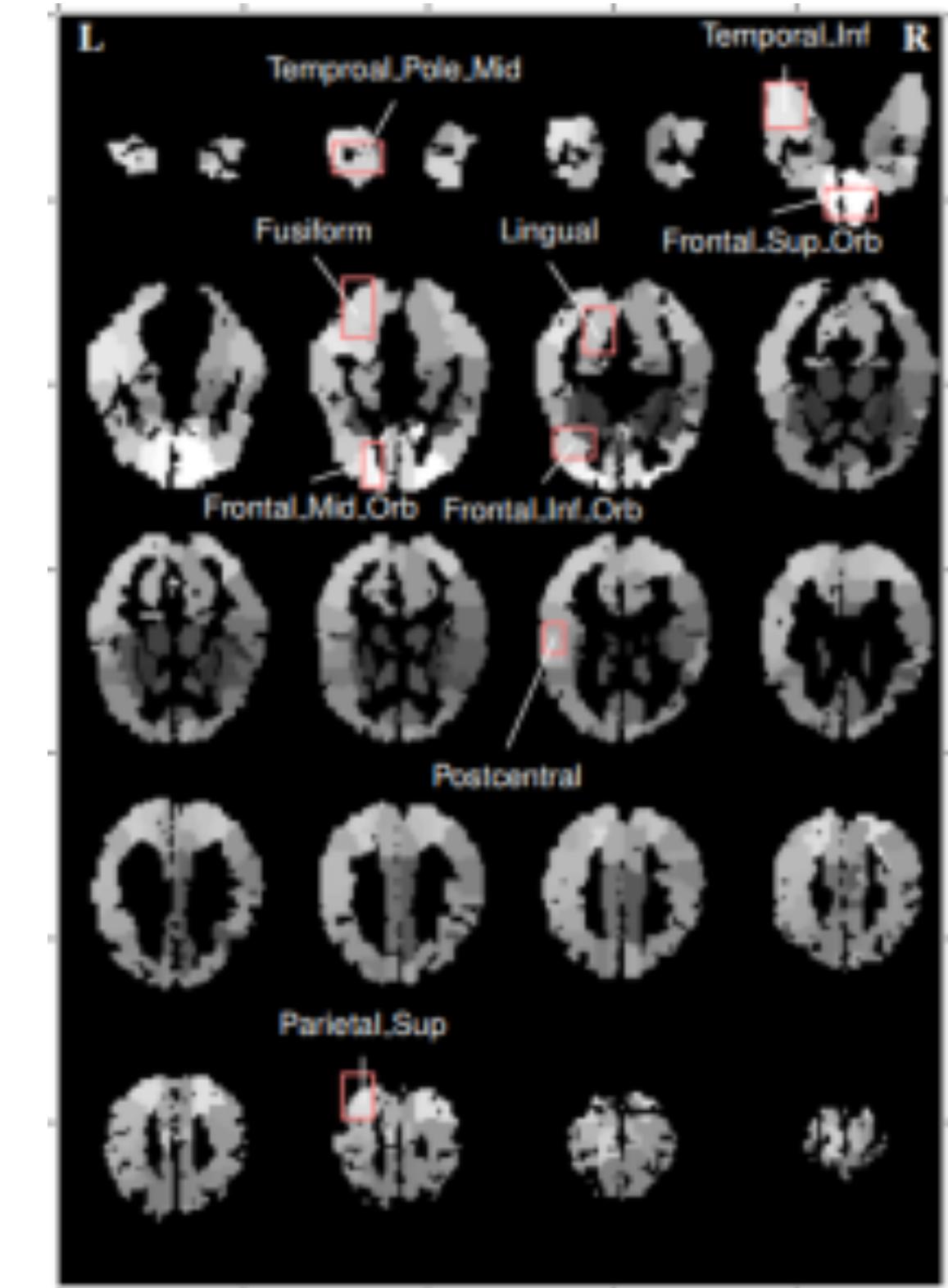
LSTM架构的认知解释

人阅读和机器阅读时的神经元活动是否可以相互预测？

LSTM架构在认知角度是否合理？



Model	Cosine Dist.	Similarity
Random	-0.128	0.436
BoW(tf-idf)	0.184	0.592
AveEmbedding	0.634	0.817
RNN_hidden	0.016	0.508
LSTM_hidden	0.224	0.612
LSTM_memory	0.724	0.862

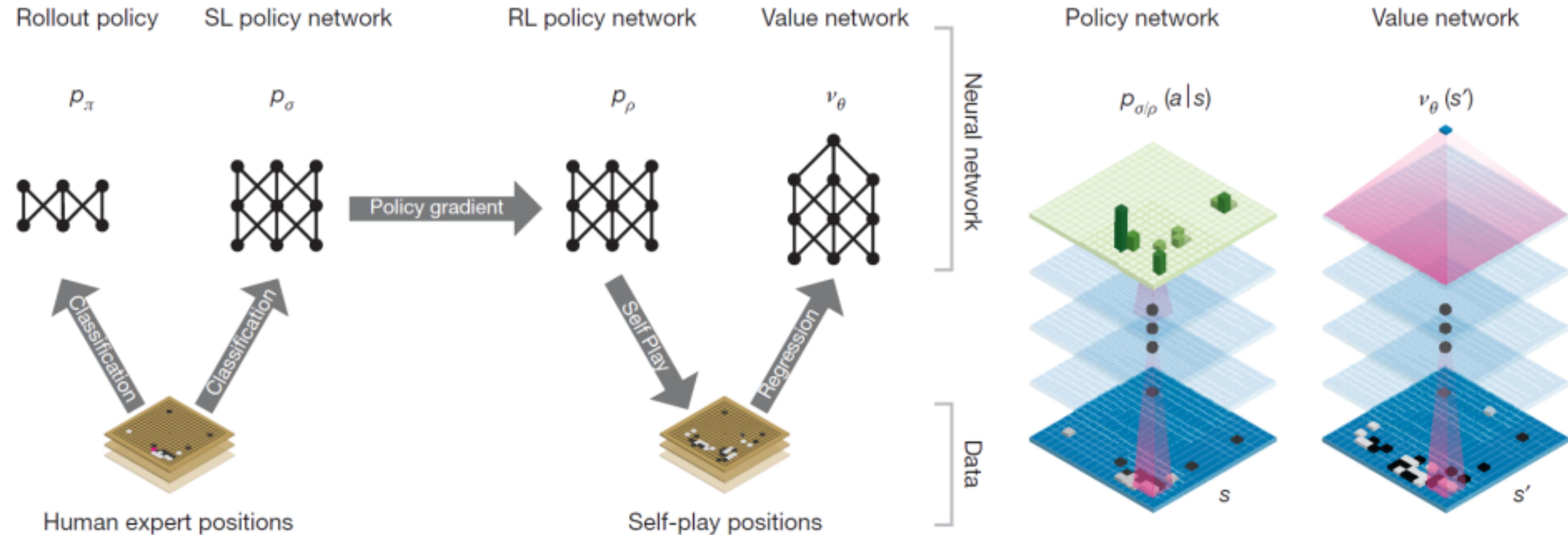


在围棋上的应用

| AlphaGo

目前在GoRating上已经超越柯洁、李世石等人排名世界第一。

在目标确定、规则明确的任务中，（弱）人工智能击败人类是必然的



在.....省电上的应用

| Google DeepMind

用于操控计算机服务器和相关设备（例如冷却系统）来管理部分数据中心，从而减少**15%**能耗



2014年总能耗
4,402,836兆瓦时



366,903个美国家庭x1年



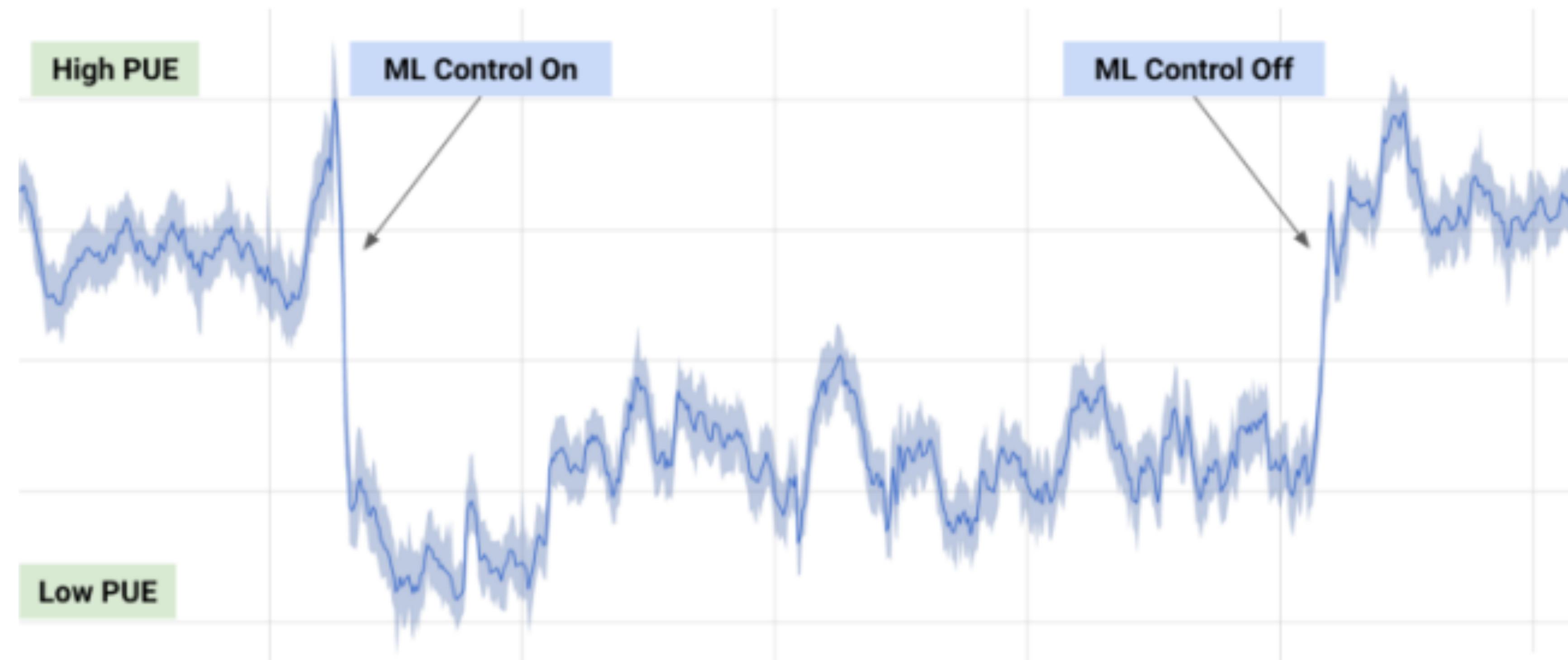
商用电价
25美元至40美元/兆瓦时

总计可节省16,500,000-26,500,000美元/年

在.....省电上的应用

| Google DeepMind

用于操控计算机服务器和相关设备（例如冷却系统）来管理部分数据中心，从而减少**15%**能耗



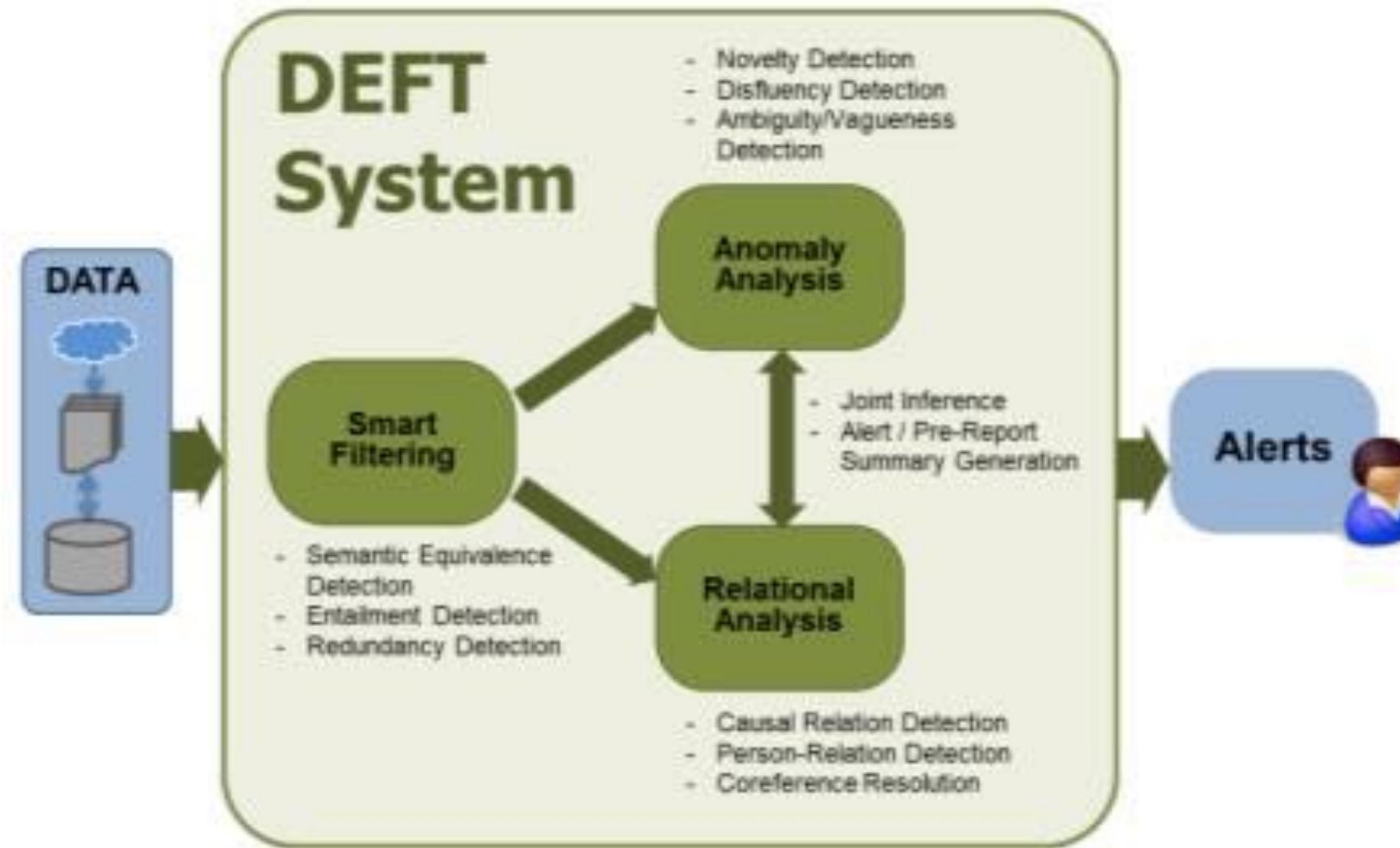
在军事领域的应用

| 美国军方早已开展相关研究与应用

2009年DARPA已着手撰写关于深度学习的报告，2010年起开始资助相关项目

2012年资助DEFT项目（Deep Exploration and Filtering of Text），对海量文本数据进行分析

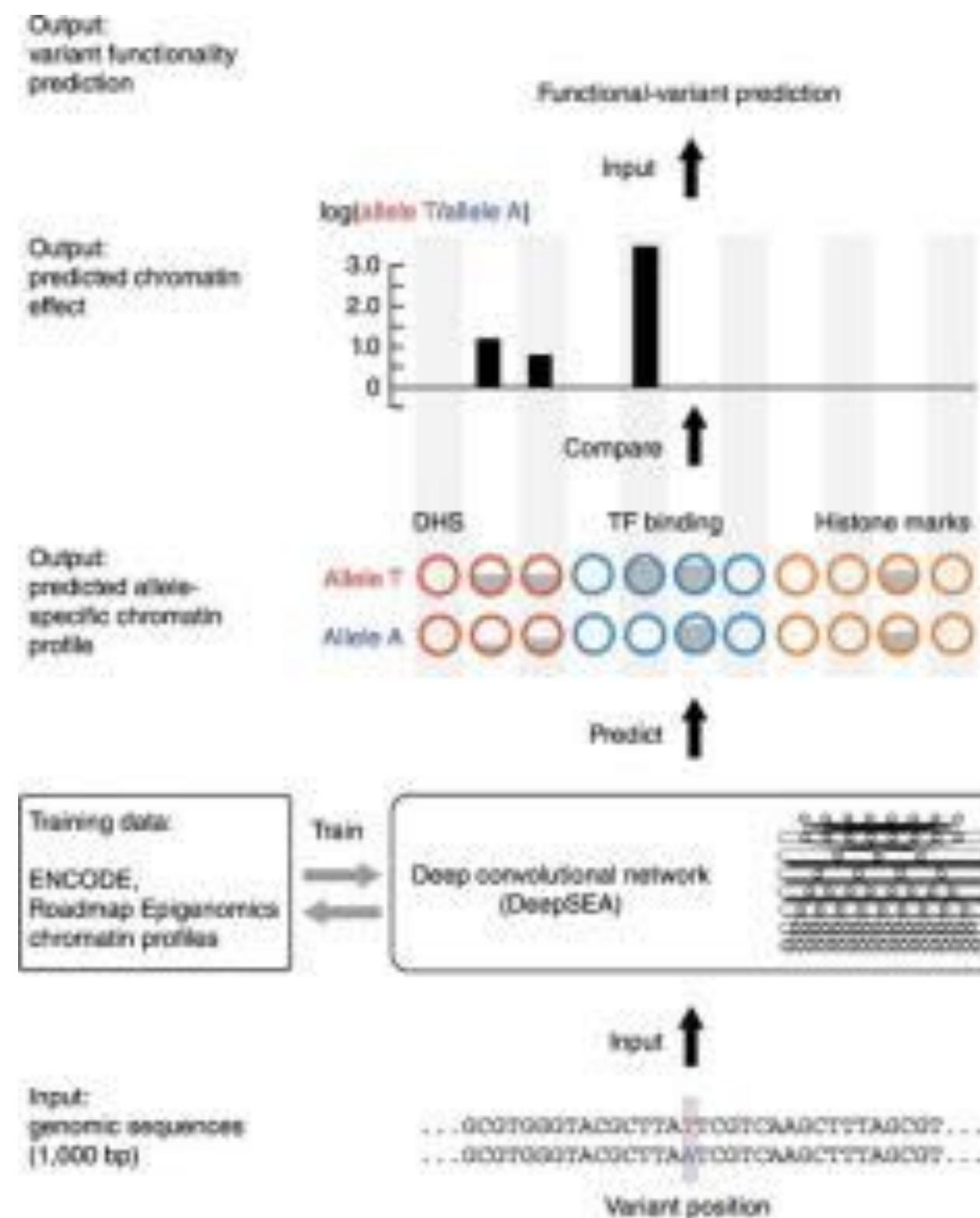
2015年资助TRACE项目（Target Recognition and Adaption in Contested Environments），对图像中的目标进行识别



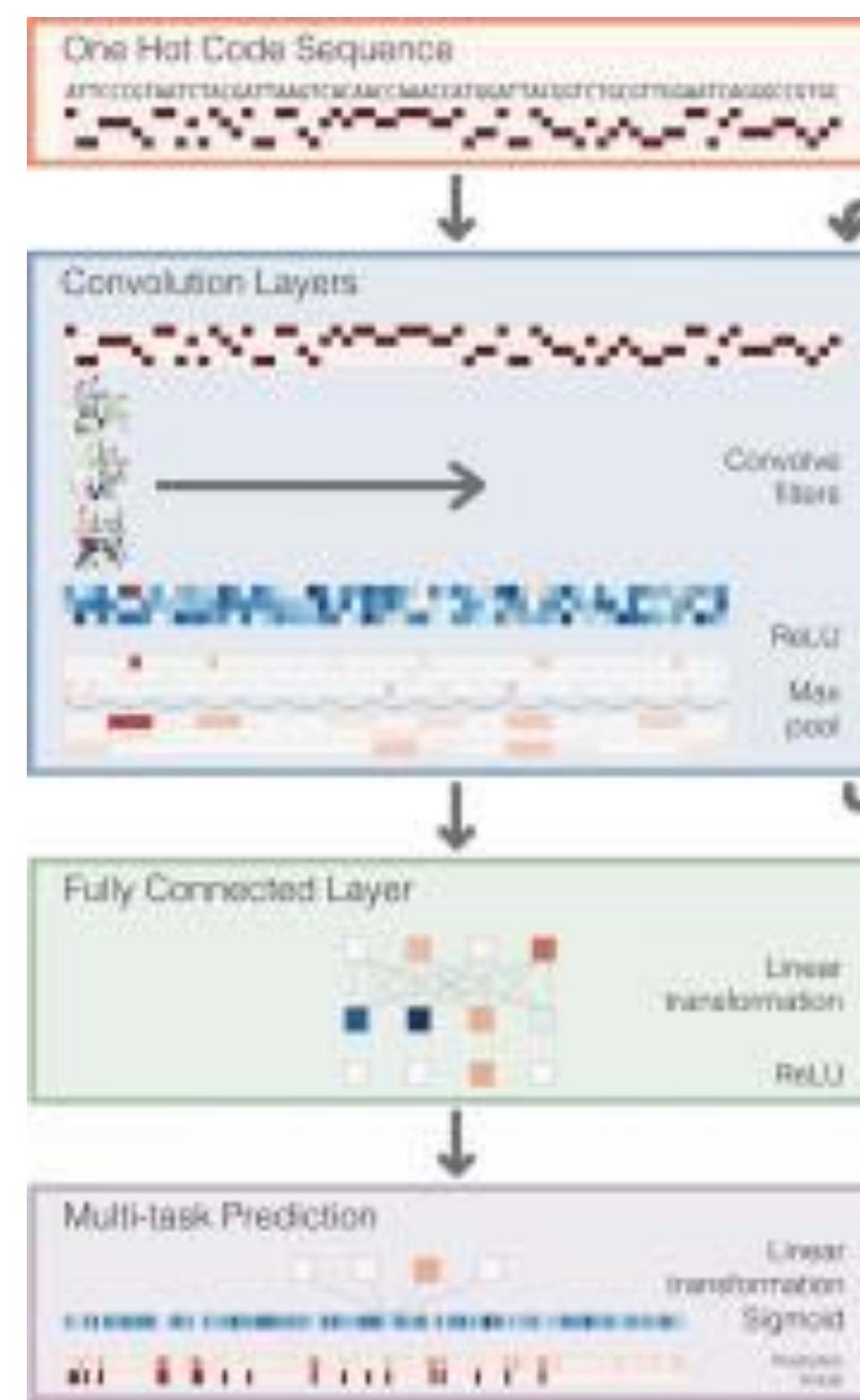
在医疗领域的应用

| 多种分析技术已经在DNA分析、癌症预测等方面产生影响

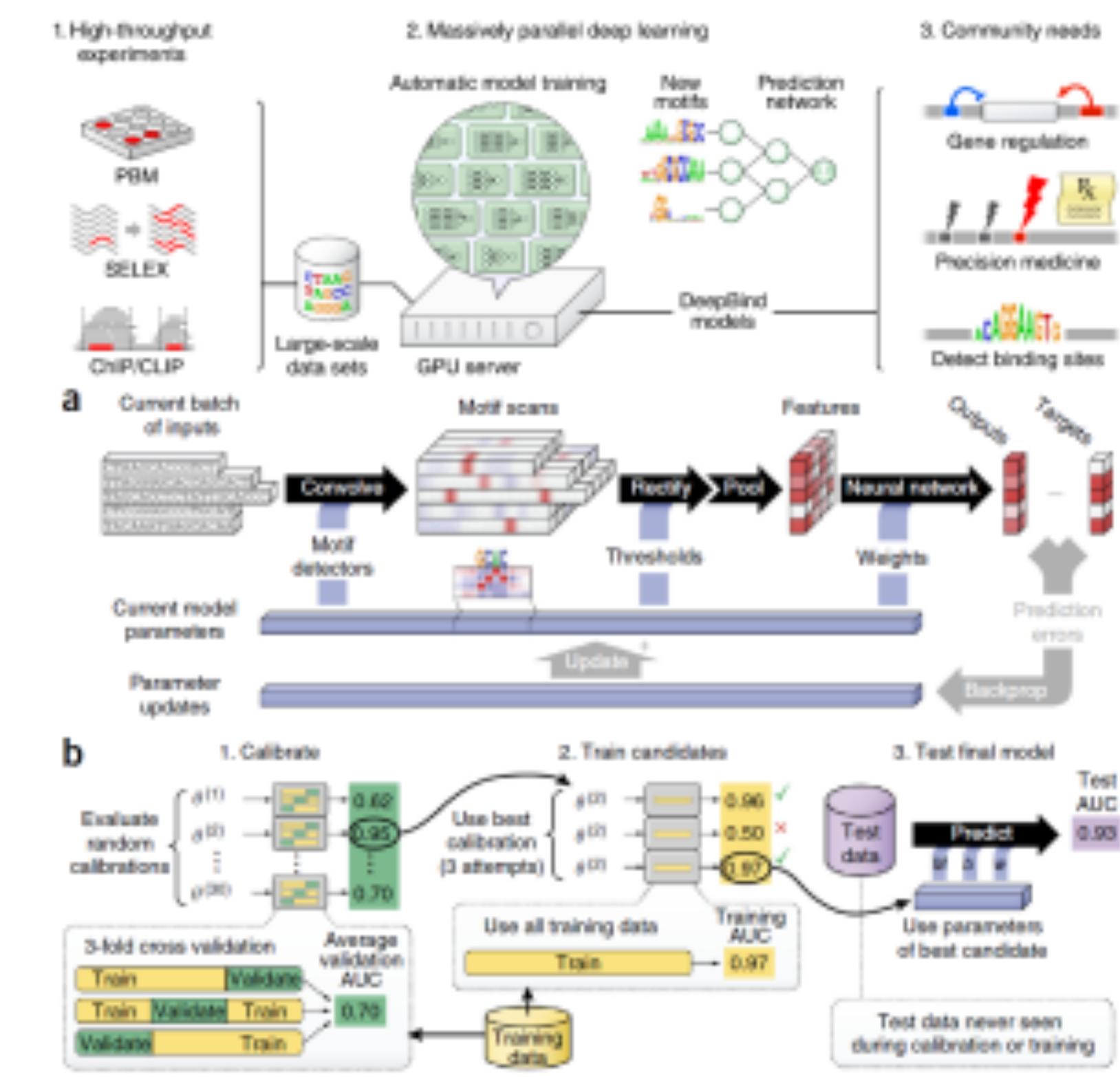
Princeton大学的DeepSEA可预测重要调控位点对单核苷酸变异的影响



Harvard大学的Basset可预测单核苷酸多态性对染色质可接近性的影响



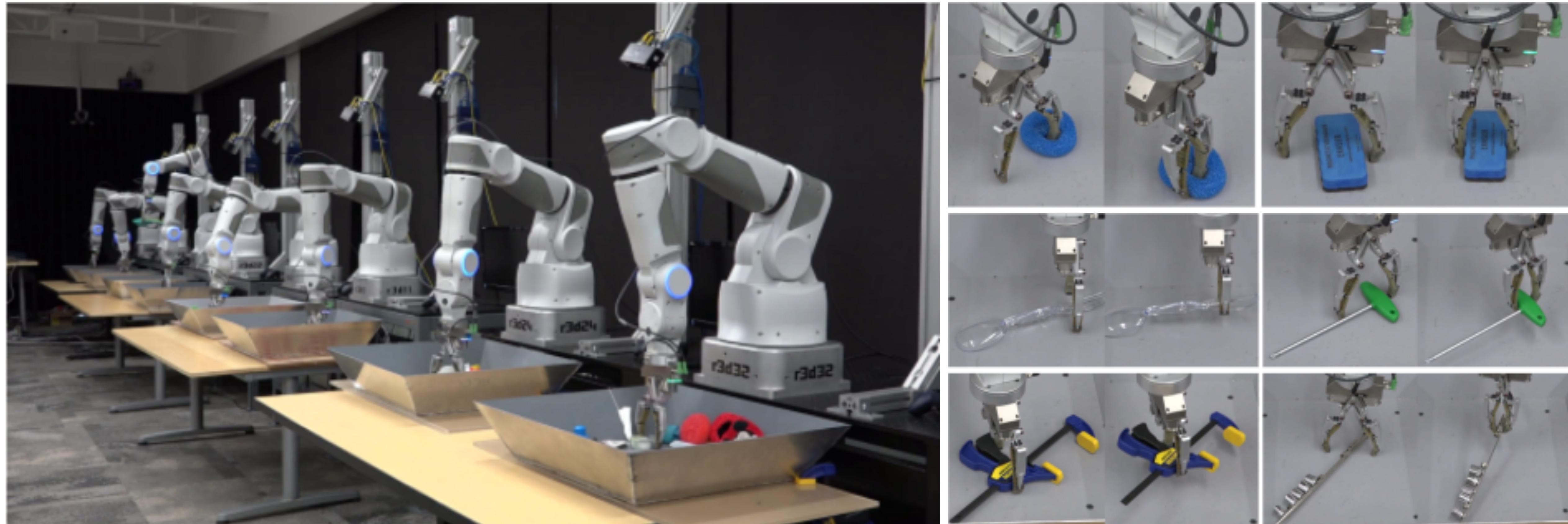
Toronto大学的DeepBind 能发现RNA与DNA上的蛋白结合位点，预测突变的影响



在智能制造领域的应用

| Google在制造领域的工作（2016年）

14台机械臂，80万次抓取作为训练，可实现对未见过的软硬材质、透明、不同重量、异形等多样化物件的精准抓取



深度学习后续发展可能

| 局部最优

梯度弥散问题
局部极值问题

| 计算复杂度

永远存在复杂度的问题

| 人脑机理模拟

是否人脑的机制是最合适的?

| 人工设计的可能性

在初始化时引入人工是否有意义?

| 代价函数的设计优化

重构误差的考虑、引入惩罚项

| 整个网络的设计优化

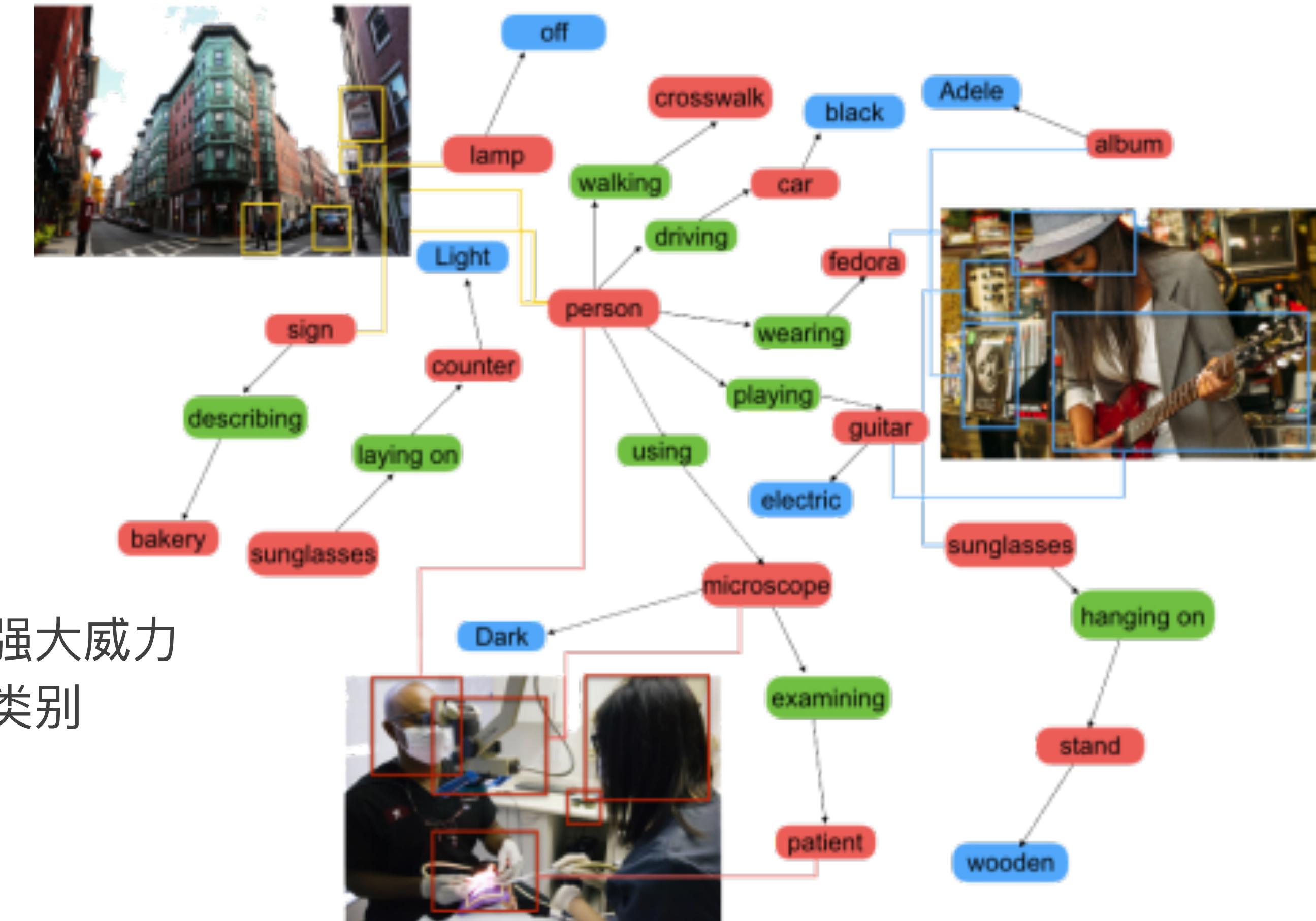
DeconvNet, DeepPose.....

深度学习后续发展可能

| 数据集

更多种类、更大规模的数据集可能出现，如Feifei Li目前在推动的视觉基因组（Visual Genome）

- 108,249张图像
 - 4.2M个区域描述
 - 1.7M个视觉问题问答答案
 - 2.1M个实体概念
 - 1.8M个属性描述
 - 1.8M个关系描述



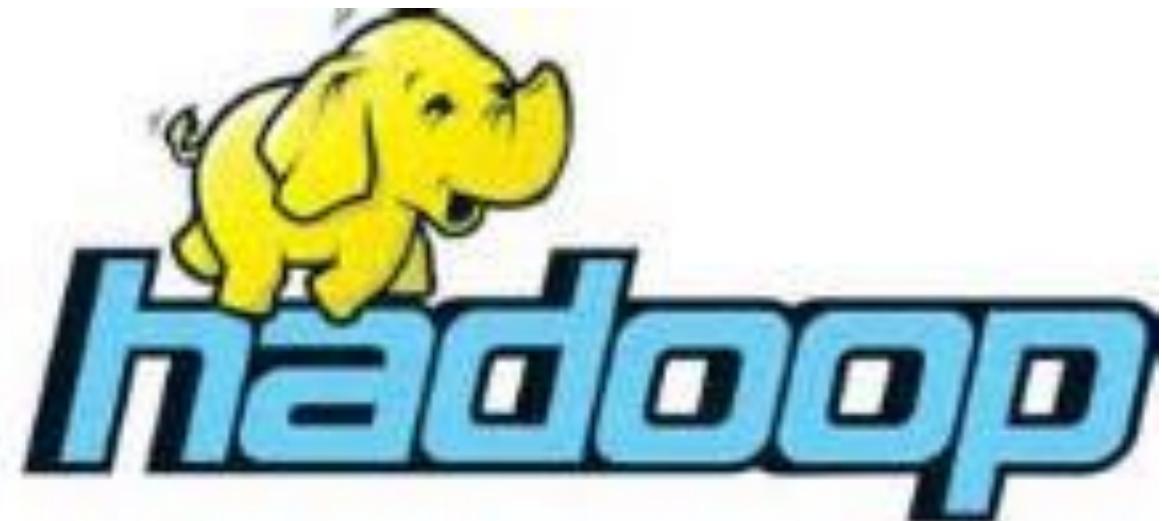
One-Shot Learning

深度学习利用需要借助大量训练数据才能实现其强大威力
人类却能仅通过有限样例就能学习到新的概念和类别

深度学习后续发展可能

| 分布式框架软件

发挥CPU+GPU的混合性能



| 指令集与计算芯片

针对深度学习优化的新架构



寒武纪处理芯片

体系结构顶级会议ISCA 2016中

- 9篇与深度学习相关 (共57篇)
- 1篇为评分最高论文

| 专用处理芯片

以FPGA为主的解决方案



降低成本、降低功耗

更多类型的新处理芯片?

Tensor Processing Unit (TPU) ?

智能的三种类型

| 感知智能

对视觉、听觉、触觉等感知能力的模拟



| 认知智能

对推理、规划、决策、学习等认知能力的模拟

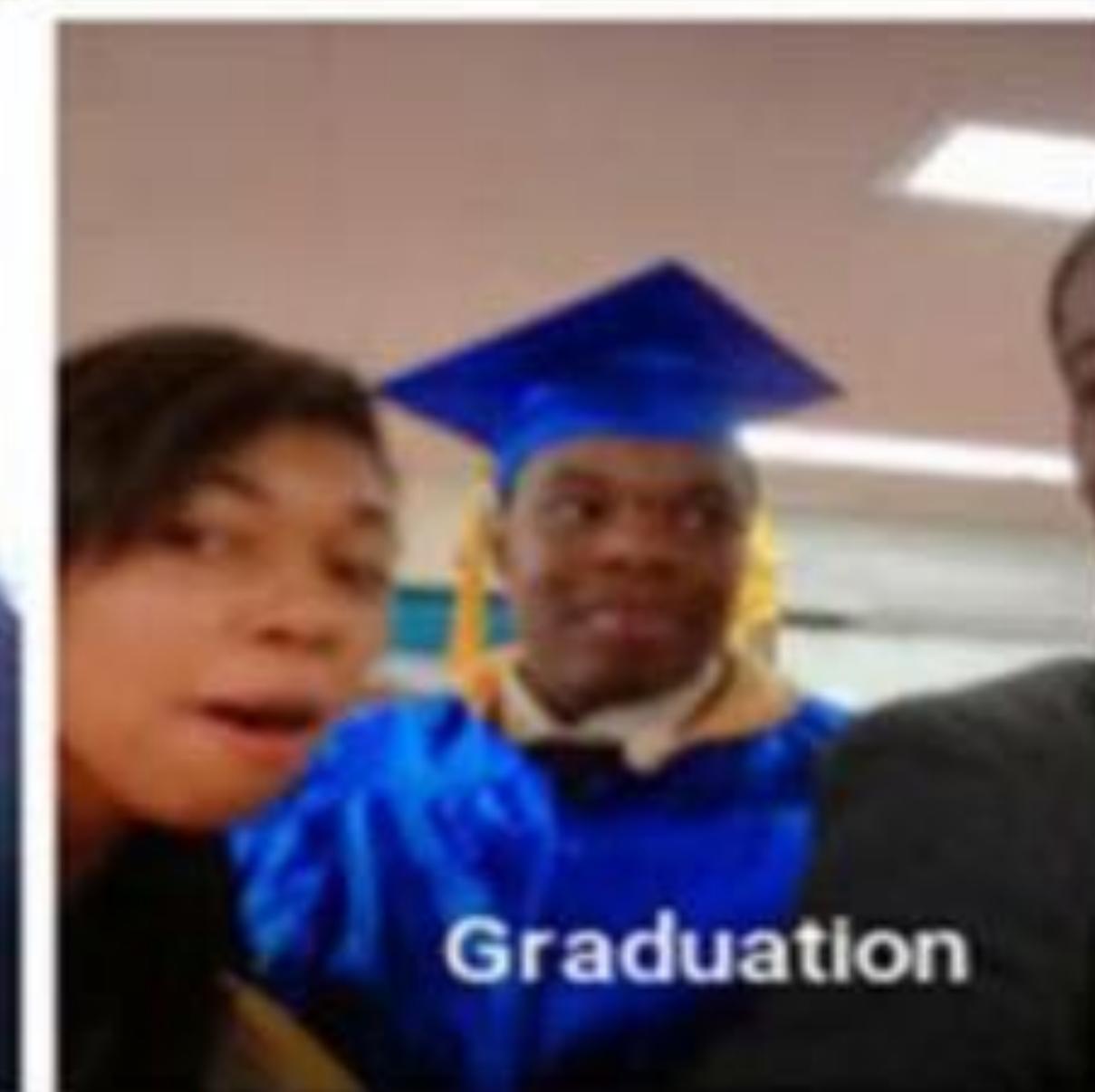
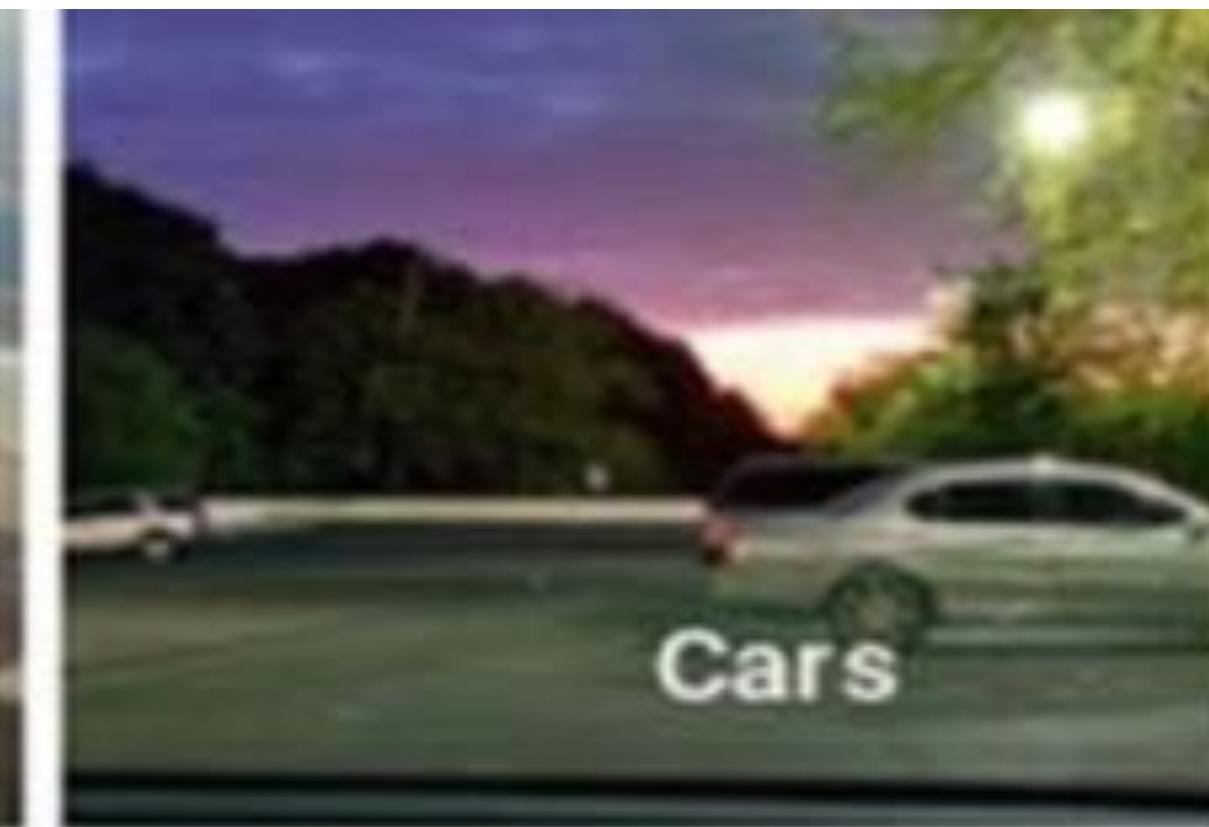


| 创造性智能

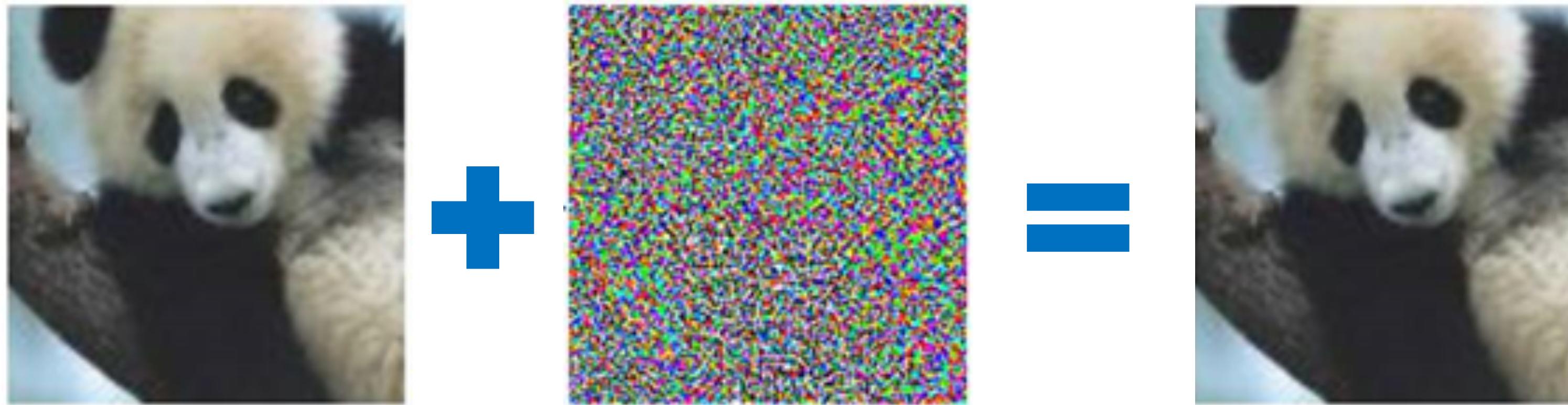
对灵感、顿悟等能力的模拟



深度学习已经解决一切了吗？



深度学习已经解决一切了吗？



A. 机判为**熊猫**
(正确)

小噪声扰动

B. 机判为**猿猴**
(错误)

深度学习已经解决一切了吗？



Chap 7 - Neural Network

- Recap
- Regularization
- Batch Normalization



Back-Propagation

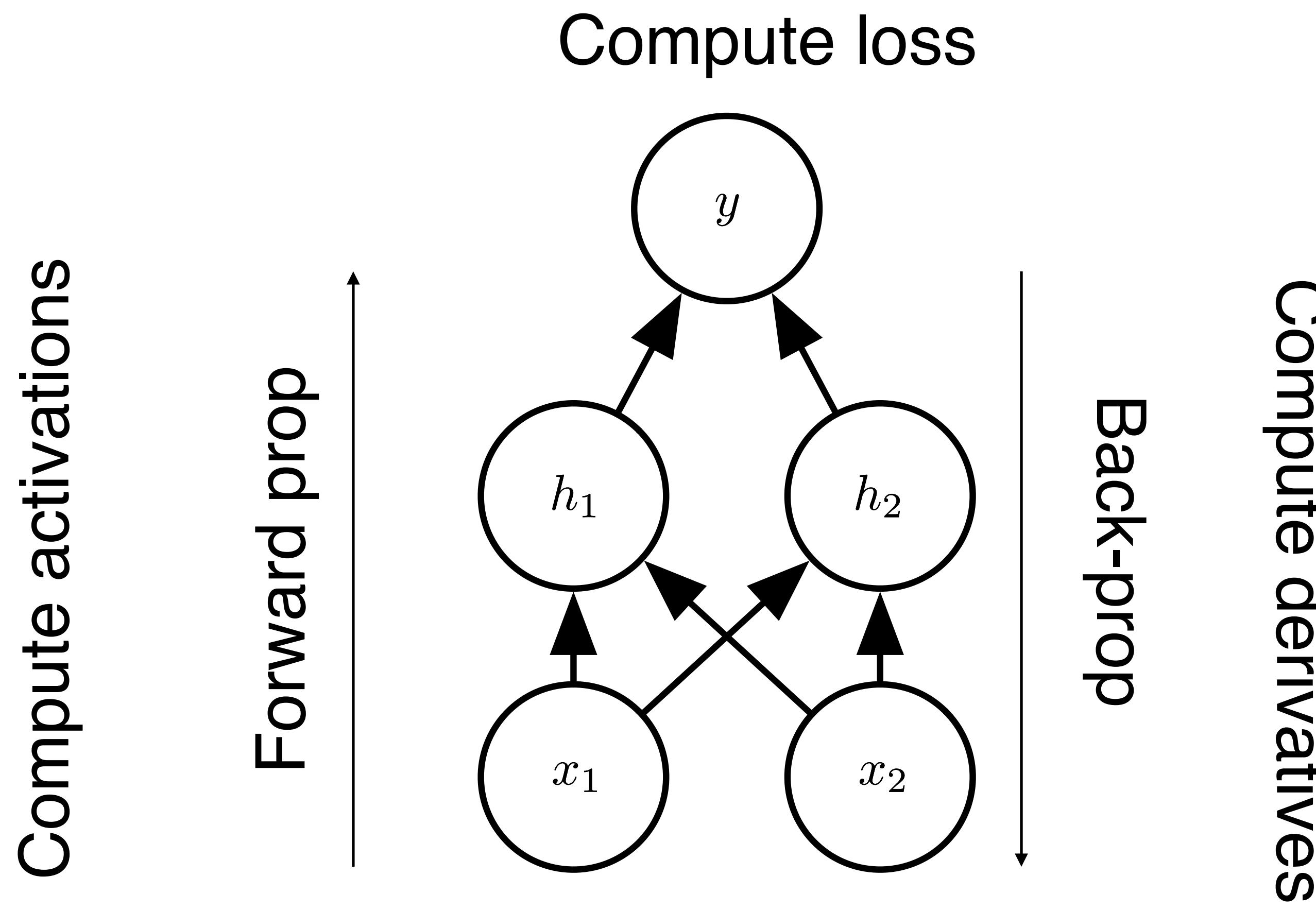
- Back-propagation is “just the chain rule” of calculus

$$\frac{dz}{dx} = \frac{dz}{dy} \frac{dy}{dx}. \quad (6.44)$$

$$\nabla_{\mathbf{x}} z = \left(\frac{\partial \mathbf{y}}{\partial \mathbf{x}} \right)^\top \nabla_{\mathbf{y}} z, \quad (6.46)$$

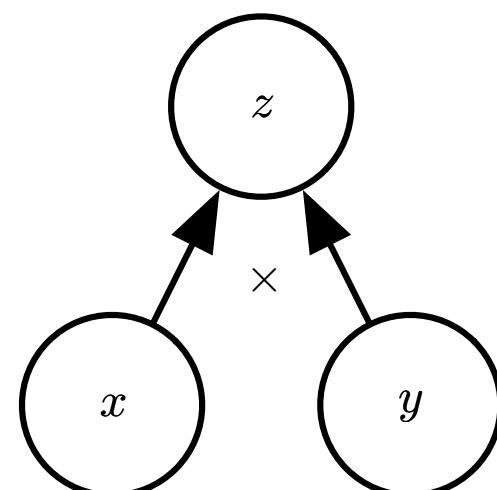
- But it's a particular implementation of the chain rule
 - Uses dynamic programming (table filling)
 - Avoids recomputing repeated subexpressions
 - Speed vs memory tradeoff

Simple Back-Prop Example

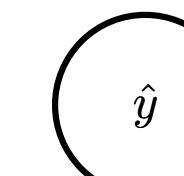


Computation Graphs

Multiplication

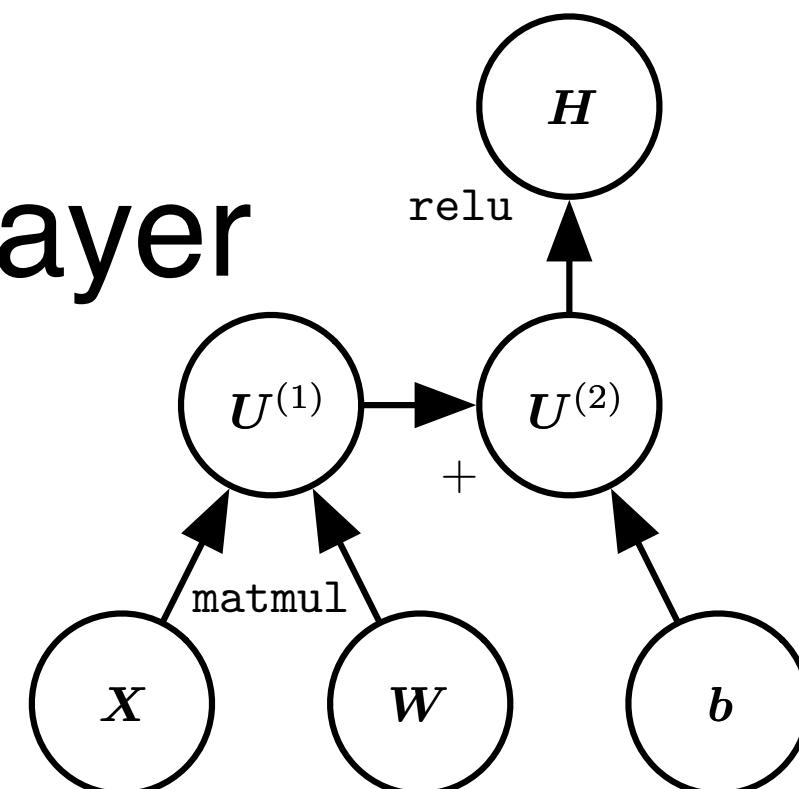


(a)



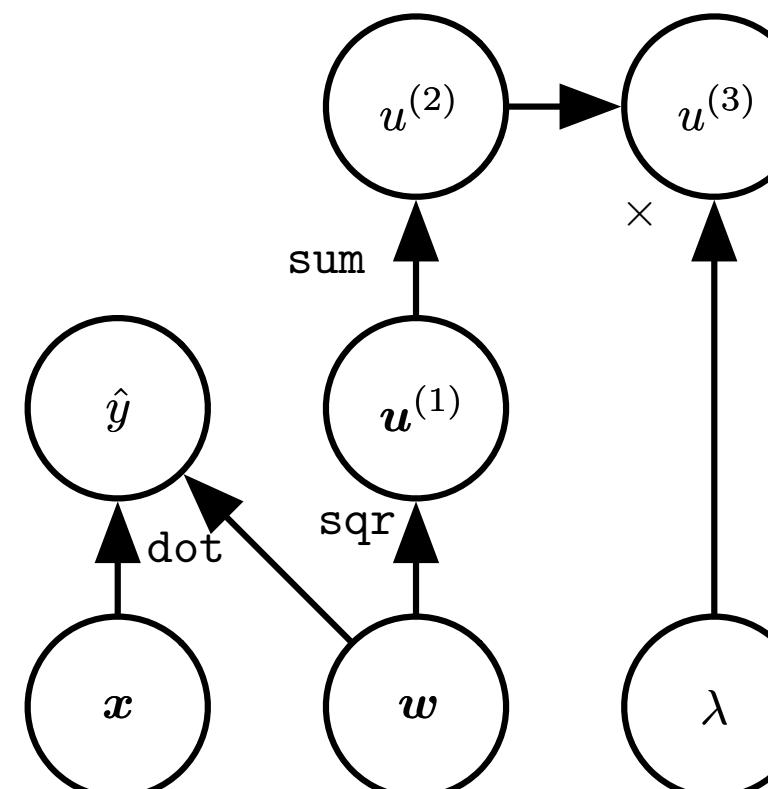
(b)

ReLU layer



(c)

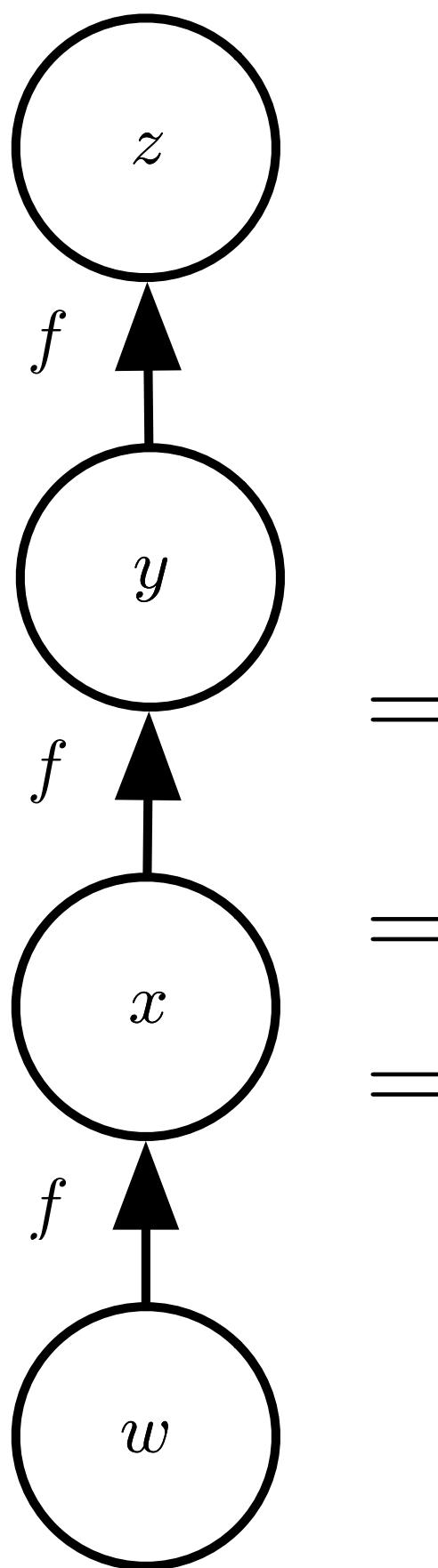
Logistic regression



(d)

Figure 6.8

Repeated Subexpressions



$$\frac{\partial z}{\partial w}$$

$$= \frac{\partial z}{\partial y} \frac{\partial y}{\partial x} \frac{\partial x}{\partial w}$$

$$= f'(y) f'(x) f'(w)$$

$$= f'(f(f(w))) f'(f(w)) f'(w)$$

(6.50)

(6.51)

(6.52)

(6.53)

Back-prop avoids computing this twice

Figure 6.9

Regularization for Deep Learning



Definition of Regularization

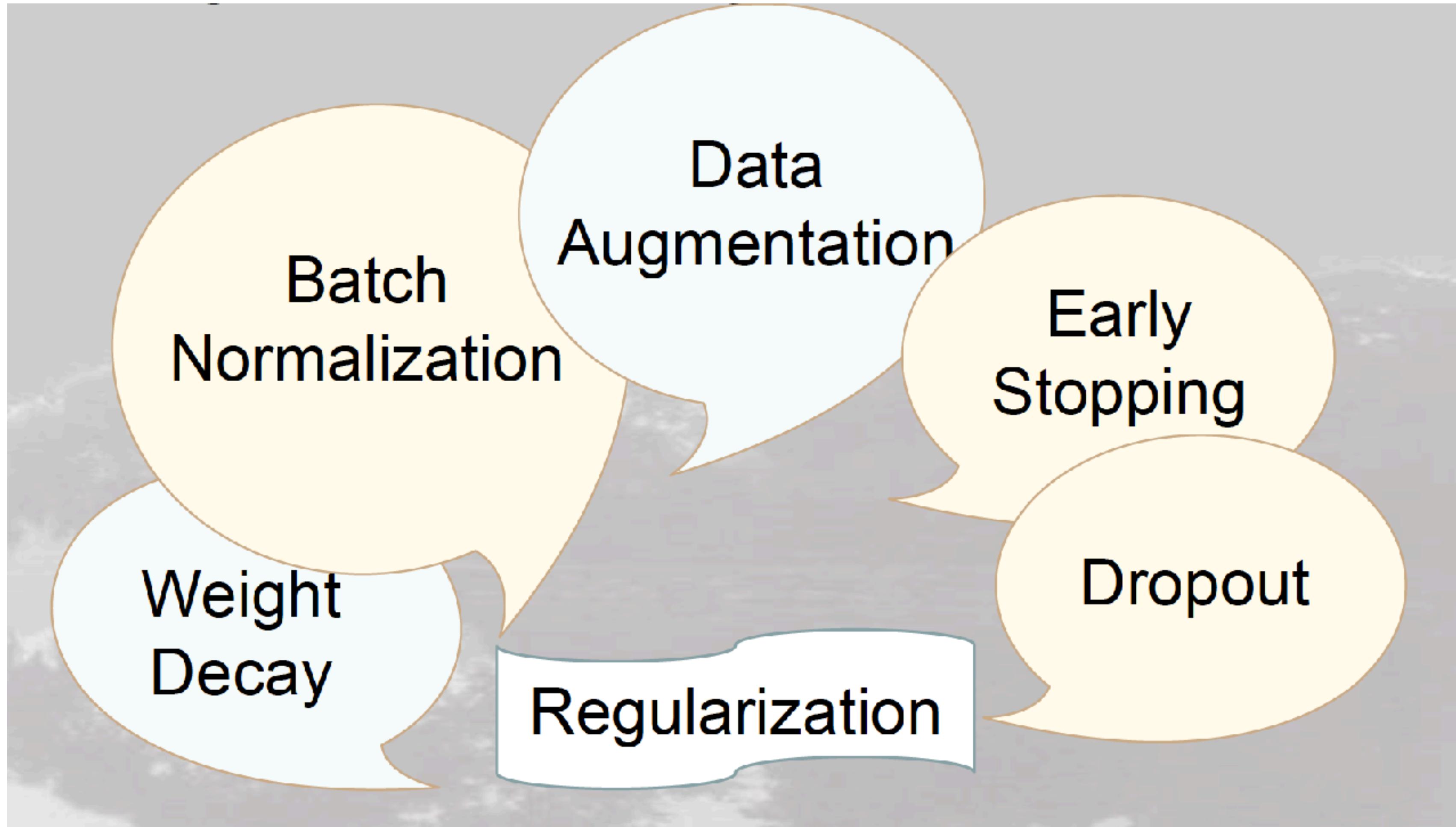
Optional subtitle

“Regularization is any modification we make to a learning algorithm that is intended to reduce its generalization error but not its training error.”



To avoid overfitting, and improve generalization performance

Optional subtitle



Some Observations of Deep Nets

- # of parameters >> # of data, hence easy to fit data
- Without regularization, deep nets also have benign generalization
- For random label or random feature, deep nets converge with 0 training error but without any generalization

Weight Decay as Constrained Optimization

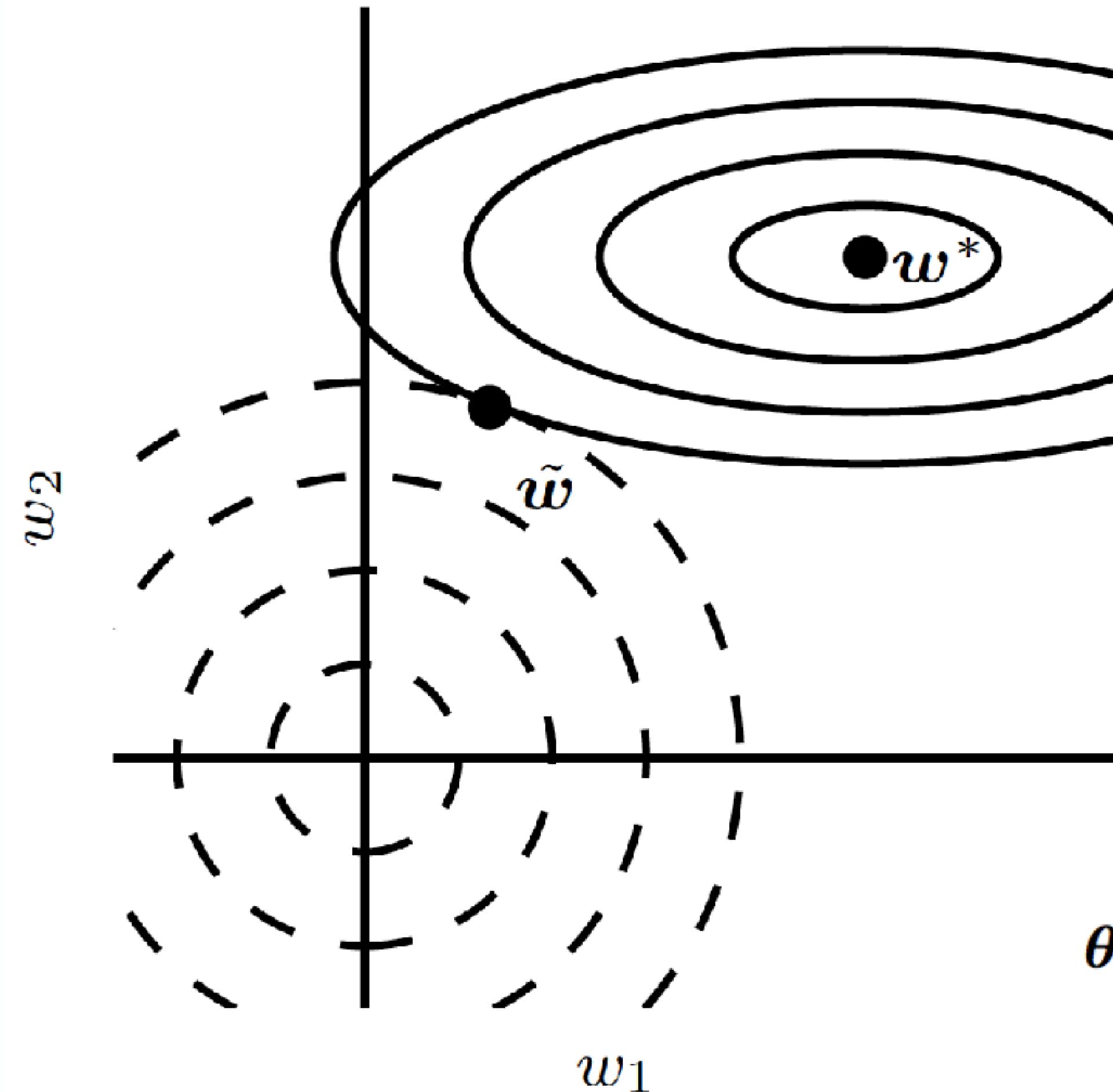


Figure 7.1

- L1: Encourages sparsity, equivalent to MAP Bayesian estimation **with Laplace prior**

- Squared L2: Encourages small weights, equivalent to MAP Bayesian estimation **with Gaussian prior**

$$\boldsymbol{\theta}_{\text{MAP}} = \arg \max_{\boldsymbol{\theta}} p(\boldsymbol{\theta} | \mathbf{x}) = \arg \max_{\boldsymbol{\theta}} \log p(\mathbf{x} | \boldsymbol{\theta}) + \log p(\boldsymbol{\theta}).$$

Dataset Augmentation

Optional subtitle



Affine
Distortion



Horizontal
flip



Noise



Random
Translation



Elastic
Deformation



Hue Shift



(Goodfellow 2016)



Fudan-SDS Confidential - Do Not Distribute



大数据学院
School of Data Science

Adversarial Examples

Optional subtitle

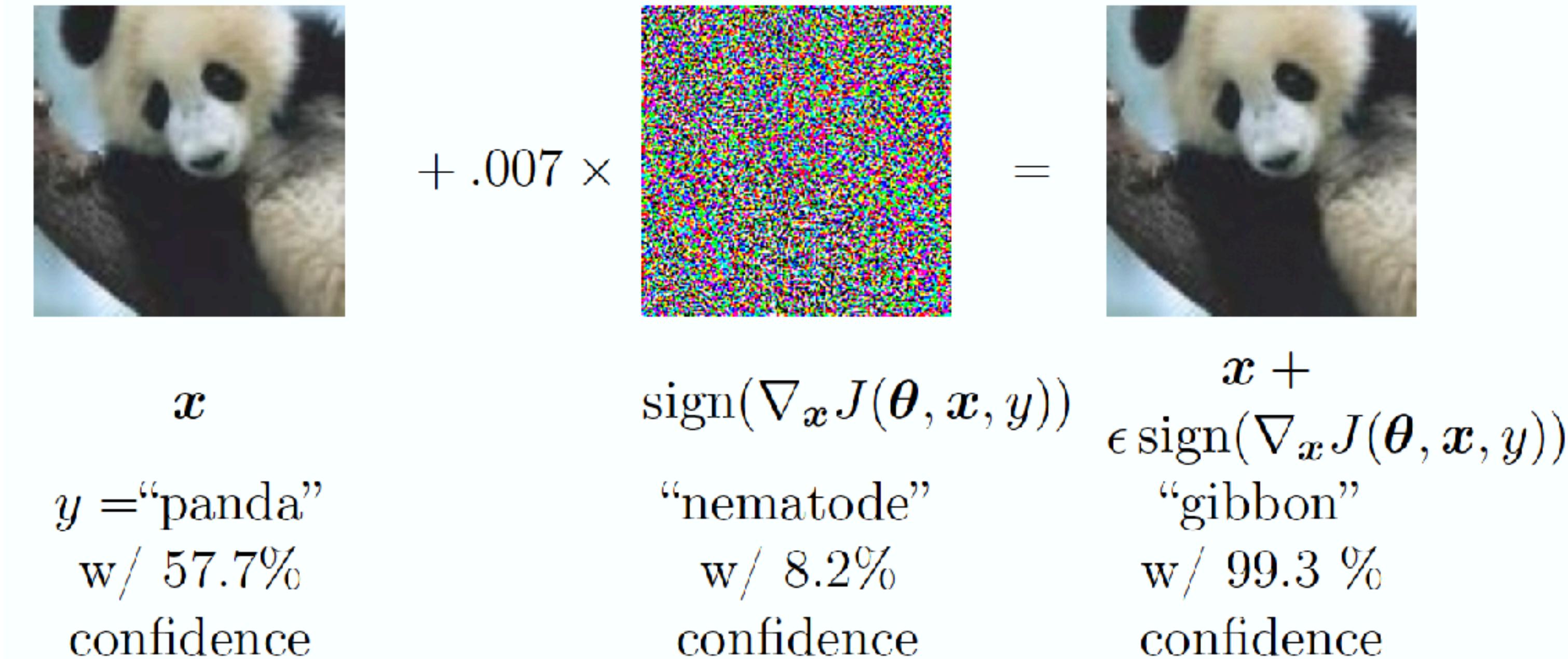


Figure 7.8

Training on adversarial examples is mostly intended to improve security, but can sometimes provide generic regularization.

ADVERSARIAL MANIPULATION OF DEEP REPRESENTATIONS

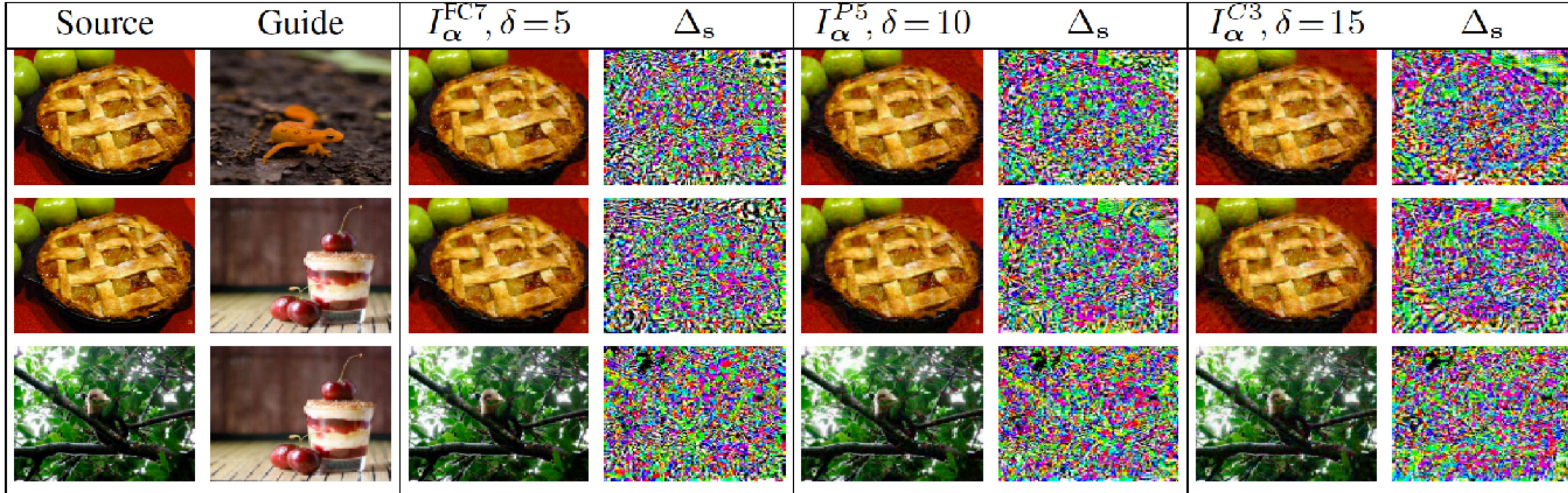


Figure 1: Each row shows examples of adversarial images, optimized using different layers of Caf-fenet (FC7, P5, and C3), and different values of $\delta = (5, 10, 15)$. Beside each adversarial image is the difference between its corresponding source image.

Let I_s and I_g denote the *source* and *guide* images. Let ϕ_k be the mapping from an image to its internal DNN representation at layer k . Our goal is to find a new image, I_{α} , such that the Euclidian distance between $\phi_k(I_{\alpha})$ and $\phi_k(I_g)$ is as small as possible, while I_{α} remains close to the source I_s . More precisely, I_{α} is defined to be the solution to a constrained optimization problem:

$$I_{\alpha} = \arg \min_I \| \phi_k(I) - \phi_k(I_g) \|_2^2 \quad (1)$$

$$\text{subject to } \| I - I_s \|_{\infty} < \delta \quad (2)$$

Learning Curves

Optional subtitle

Early stopping: terminate while validation set performance is better

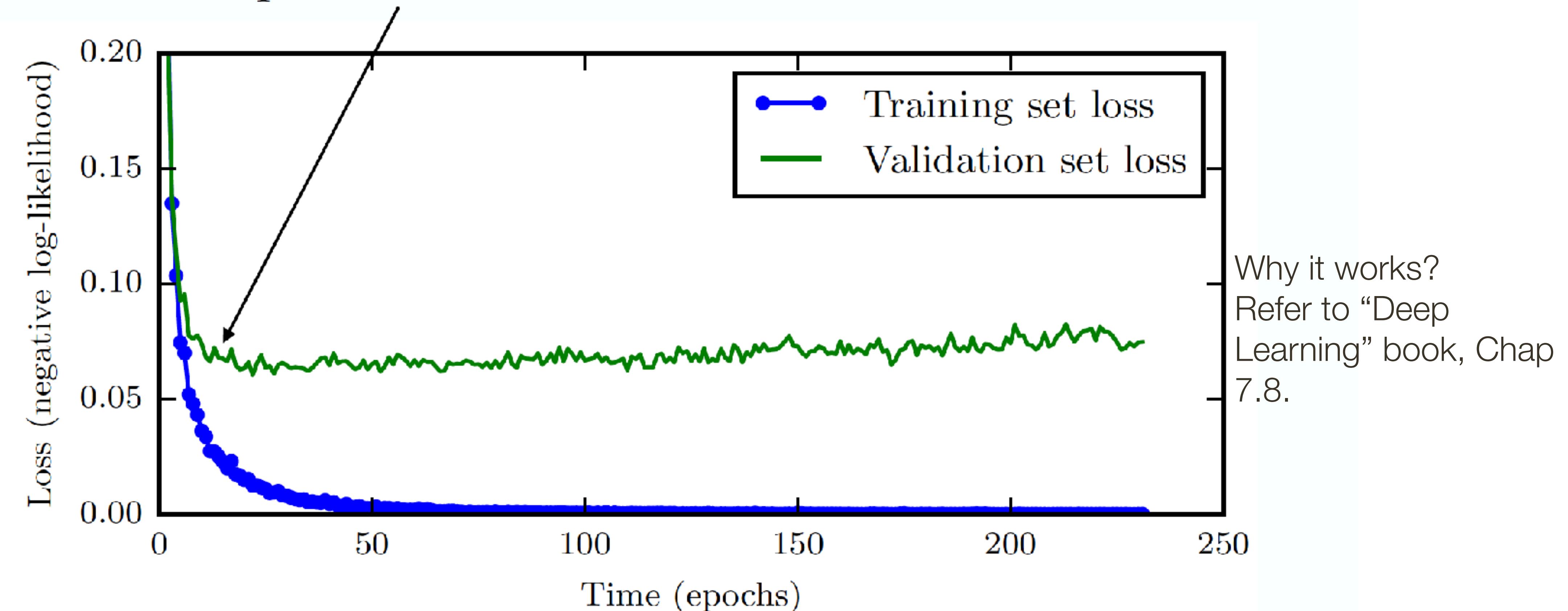


Figure 7.3

(Goodfellow 2016)



Bagging

Optional subtitle

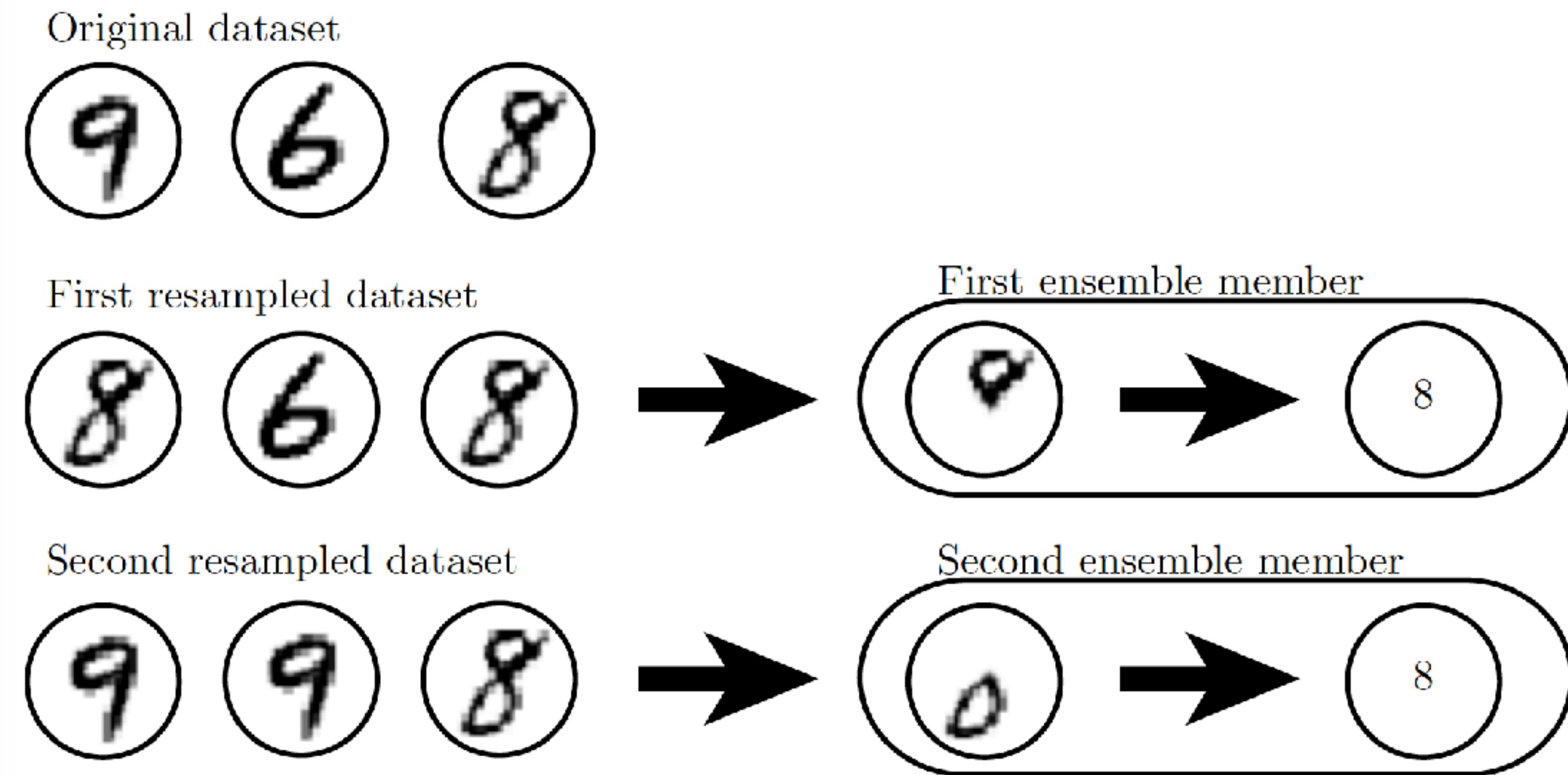


Figure 7.5

(Goodfellow 2016)



Batch Normalization

“Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift,” Ioffe and Szegedy 2015



Batch Normalization

$$Z = XW$$

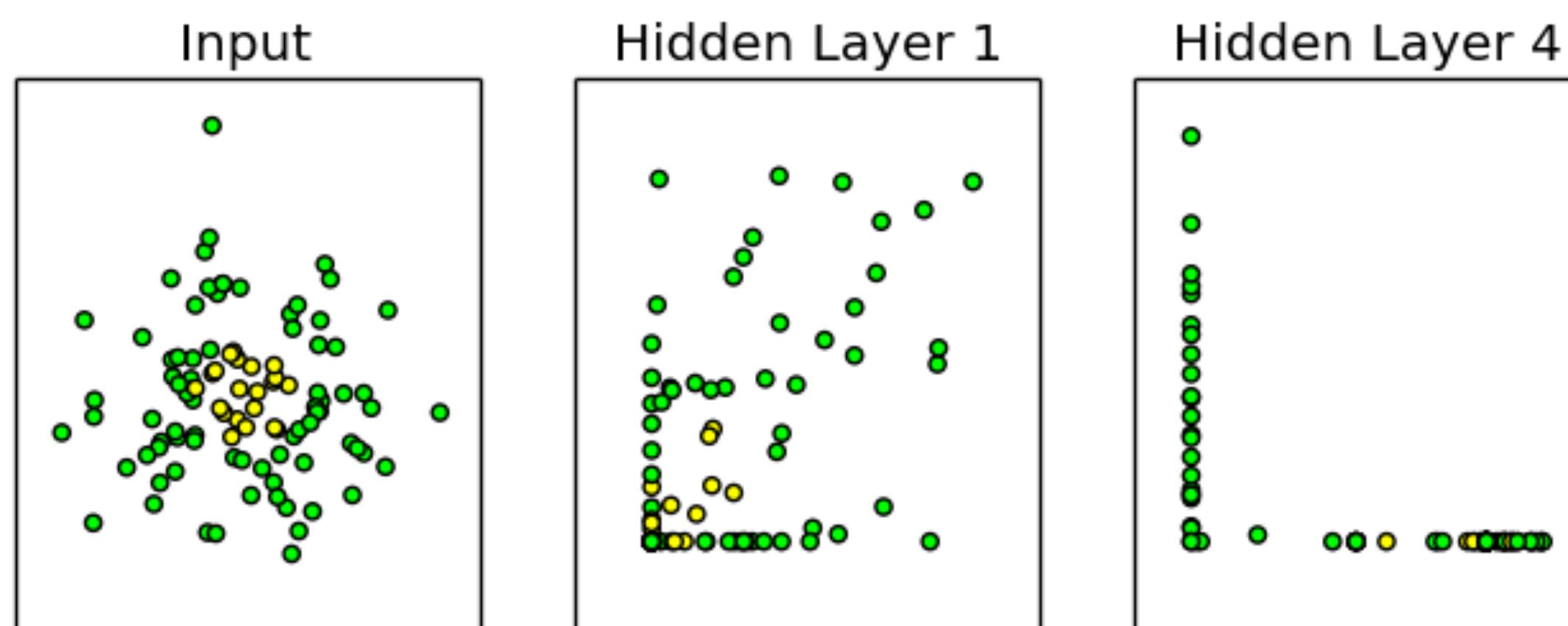
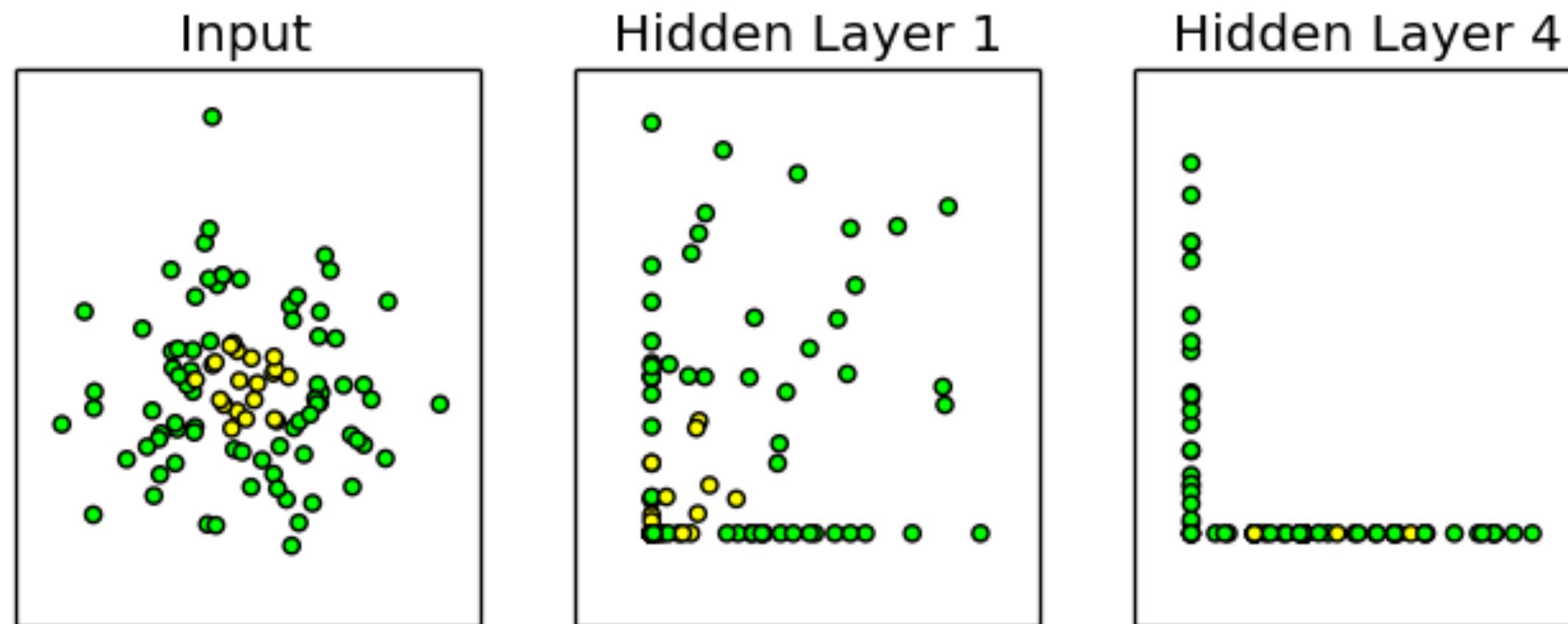
$$\tilde{Z} = Z - \frac{1}{m} \sum_{i=1}^m z_{i,:}$$

$$\hat{Z} = \frac{\tilde{Z}}{\sqrt{\epsilon + \frac{1}{m} \sum_{i=1}^m \tilde{Z}_{i,:}^2}}$$

$$H = \max\{0, \gamma \hat{Z} + \beta\}$$

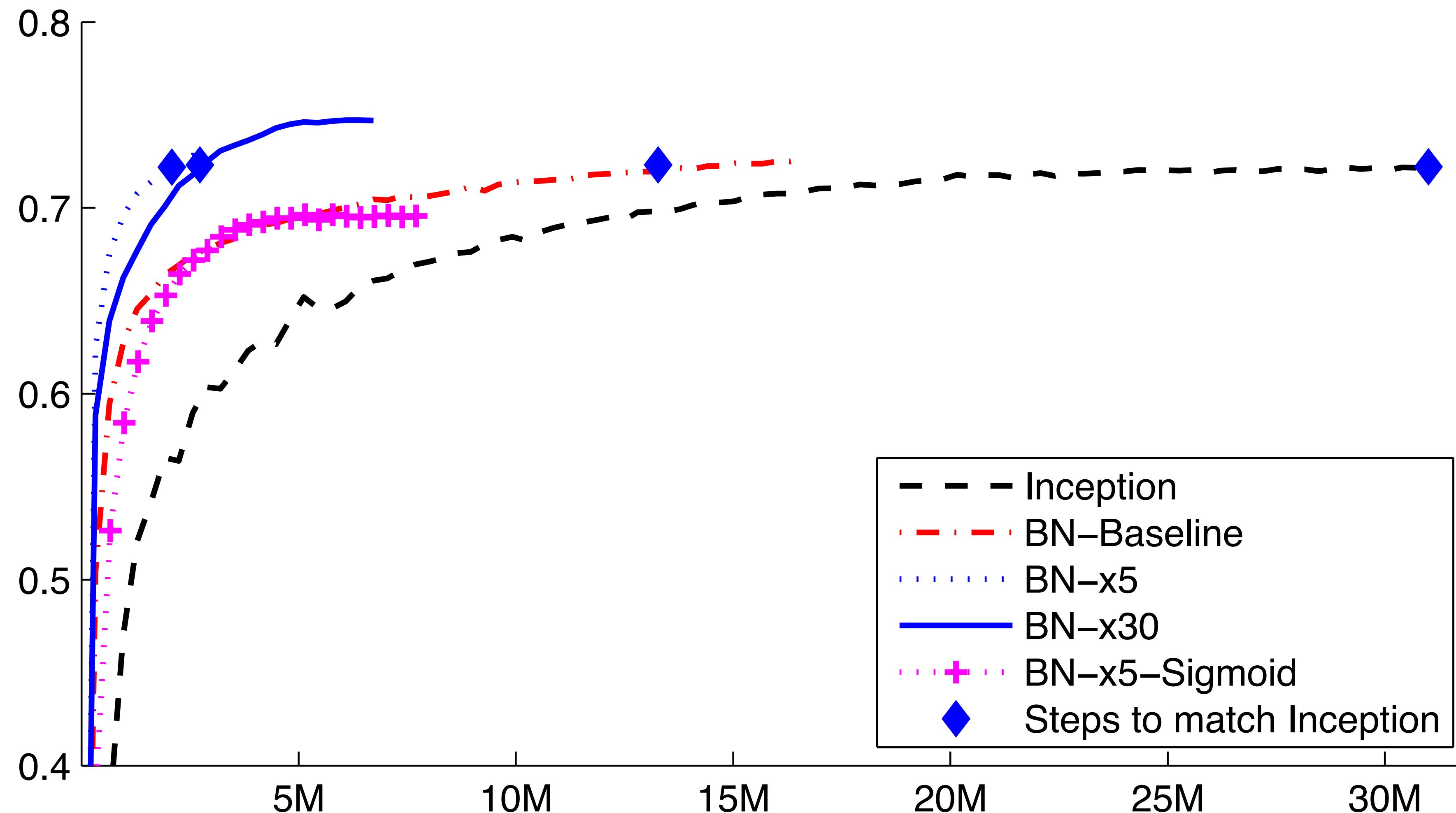
“Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift,” Ioffe and Szegedy 2015

Before SGD step



After SGD step

“Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift,” Ioffe and Szegedy 2015



“Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift,” Ioffe and Szegedy 2015