

$$\Phi\left(\text{img}_1\right) = \text{img}_2 \quad \Phi\left(\text{img}_3\right) = \text{img}_4$$

$$K\left(\text{img}_1, \text{img}_3\right) = \left(\text{img}_2\right) \cdot \left(\text{img}_4\right)$$

# Kernel-based Learning: Theoretical Foundation

Pilsung Kang

School of Industrial Management Engineering

Korea University

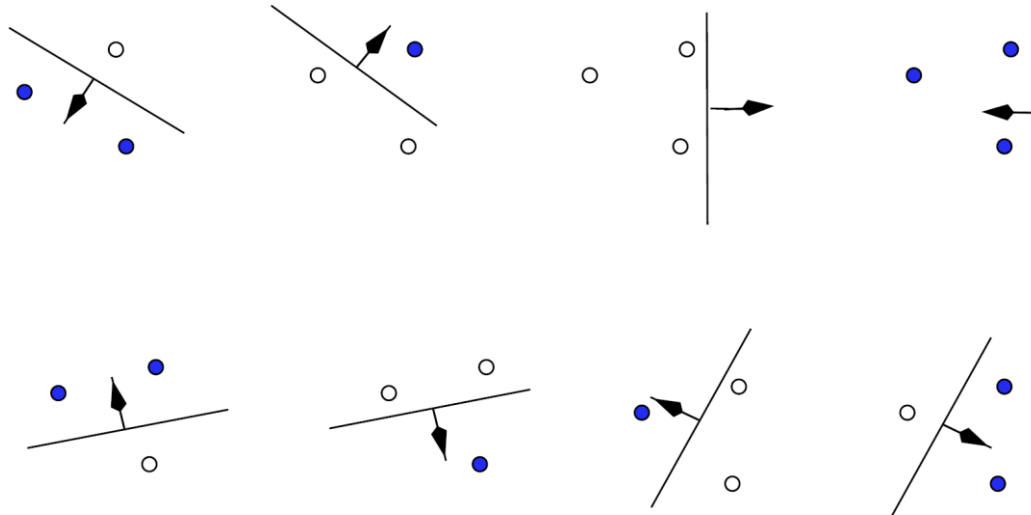
# The Concept of Shatter

- Shatter

- ✓ A set of points is said to be shattered by a class of functions if, no matter how we assign a binary label to each point, a member of the class can perfectly separate them.

- A linear classifier can shatter  $(n+1)$  instances in  $n$ -dimensional space

- ✓ 함수  $F$ 는  $n$ 개의 points를 Shatter할 수 있다  $\rightarrow$  함수  $F$ 에 의해  $n$ 개의 point는 임의의  $+1$  또는  $-1$ 을 Target value로 하는 분류 경계면의 생성이 가능하다.

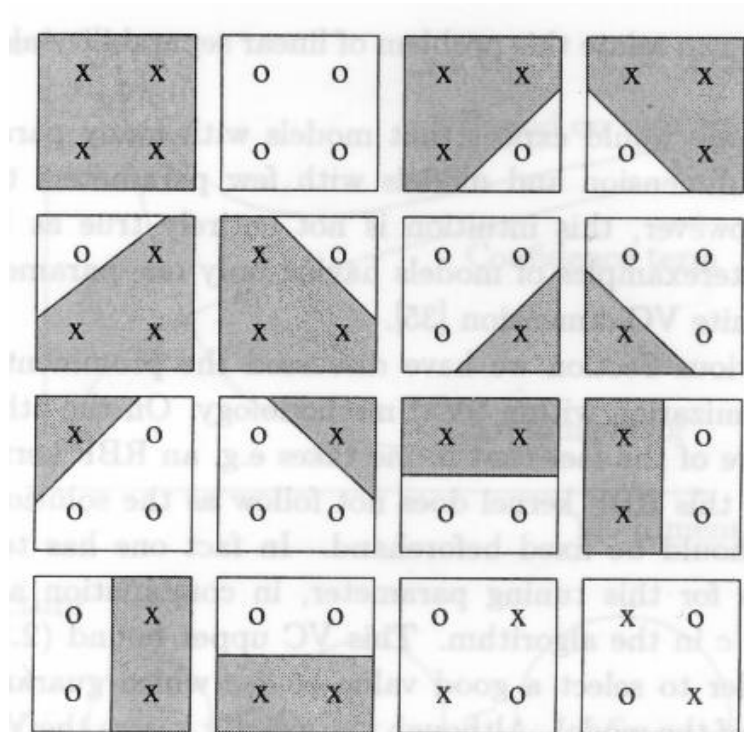


# The Concept of Shatter

- Shatter

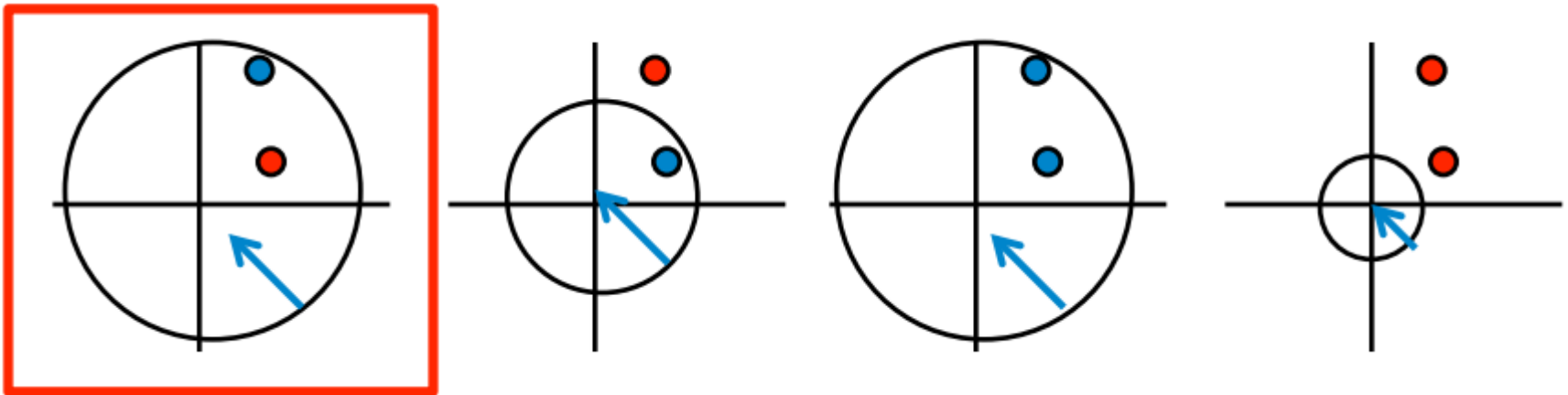
✓ A set of points is said to be shattered by a class of functions if, no matter how we assign a binary label to each points, a member of the class can perfectly separate them.

- Can a linear classifier shatter  $(n+2)$  instances in  $n$ -dimensional space?



# The Concept of Shatter

- Shatter
  - ✓ A set of points is said to be shattered by a class of functions if, no matter how we assign a binary label to each points, a member of the class can perfectly separate them.
  - A circle cannot shatter 2 instances in 2-dimensional space

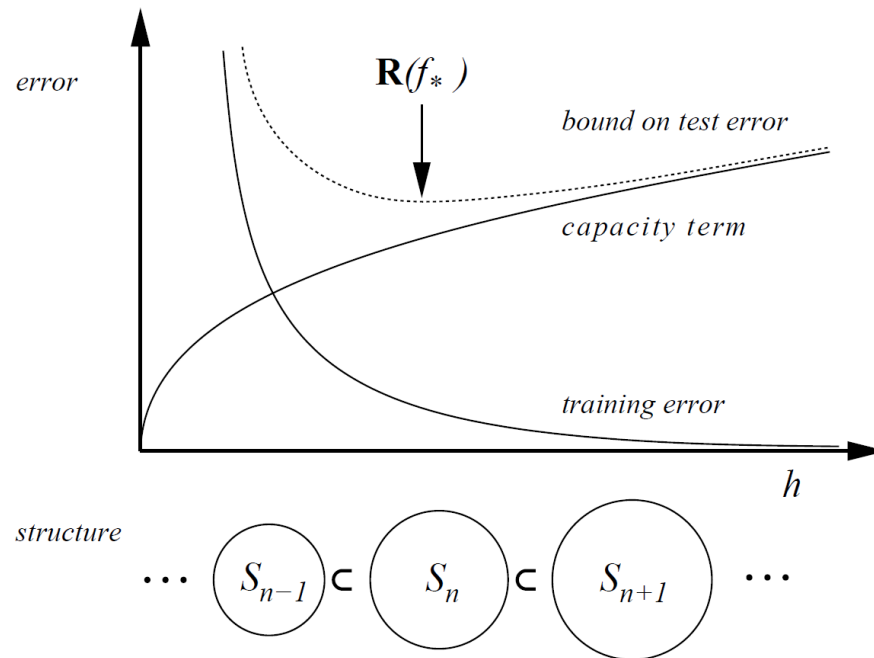


# Vapnik-Chervonekis (VC) Dimension

- VC dimension
  - ✓ Measures the capacity of a hypothesis space
  - ✓ Capacity is a measure of complexity and measures the expressive power, richness or flexibility of a set of functions by assessing how wiggly its members can be
  - ✓ The maximum number of points that can be shattered by  $H$  is called **VC dimension**

# ERM vs. SRM

- Structural Risk Minimization (SRM)



- ✓ An inductive principle for model selection used for learning from finite training data
- ✓ Describe a general model of capacity control and provides a trade-off between **hypothesis space complexity (VC dim.)** and the **quality of fitting the training data (empirical error)**

# ERM vs. SRM

- Structural Risk Minimization

Let  $h$  denote the VC dimension of the function class  $F$  and let  $R_{emp}$  be defined as follows using the 0/1 loss.

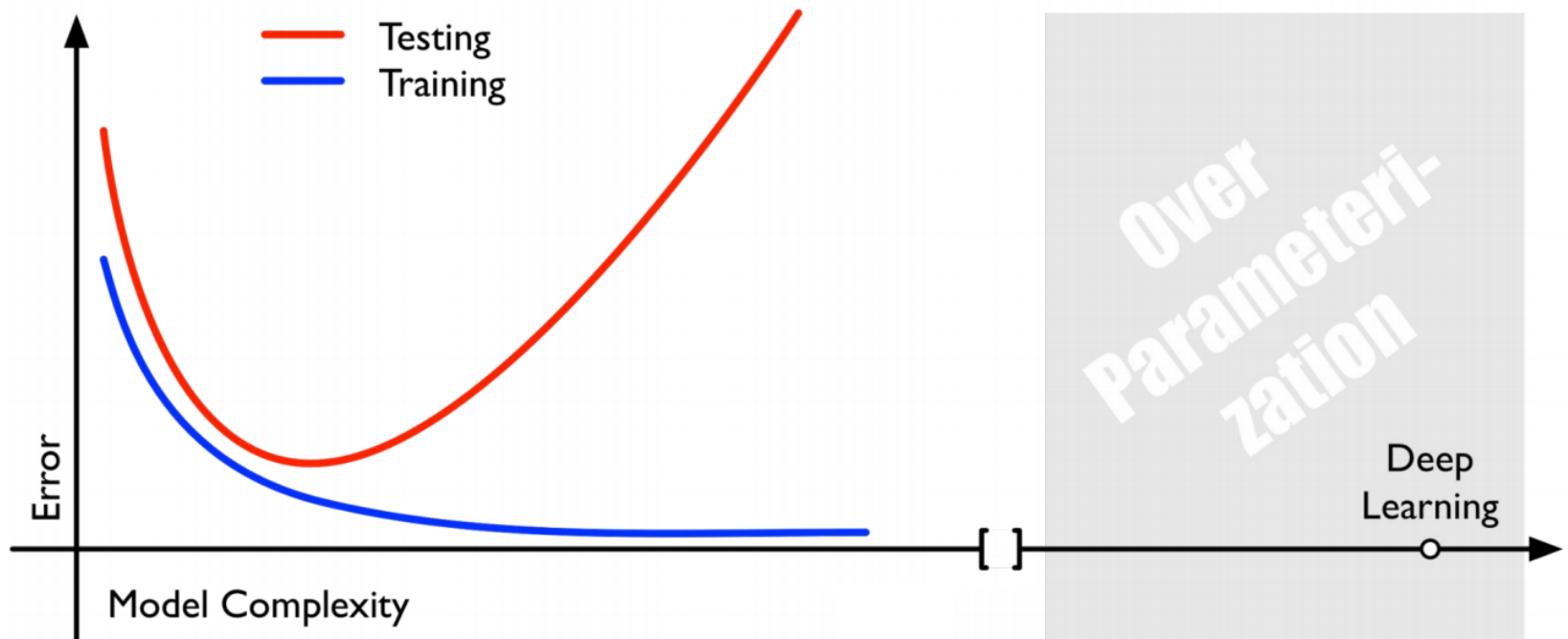
$$R_{emp}[f] = \frac{1}{n} \sum_{i=1}^n L(f(x_i), y_i)$$

For all  $\delta > 0$  and  $f \in F$  the inequality bounding the risk below holds with probability of at least  $1 - \delta$  for  $n > h$ .

$$R[f] \leq R_{emp}[f] + \sqrt{\frac{h \left( \ln \frac{2n}{h} + 1 \right) - \ln \left( \frac{\delta}{4} \right)}{n}}$$

# ERM vs. SRM

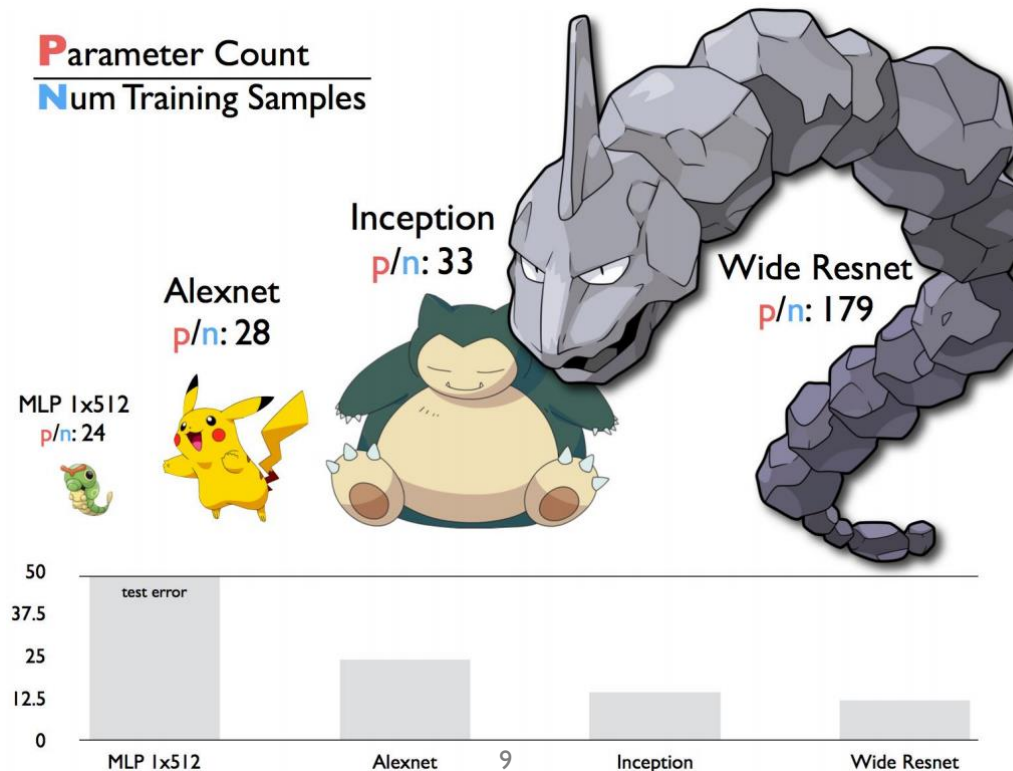
- Structural Risk Minimization (SRM)
  - ✓ Trade-off between **hypothesis space complexity (VC dim.)** and the **quality of fitting the training data (empirical error)**
  - ✓ Understanding Deep Learning Requires Rethinking Generalization (Zhang et al 2017a, 2017b, 2017c, Park 2017)





# ERM vs. SRM

- Structural Risk Minimization (SRM)
  - ✓ Trade-off between **hypothesis space complexity (VC dim.)** and the **quality of fitting the training data (empirical error)**
  - ✓ Understanding Deep Learning Requires Rethinking Generalization (Zhang et al 2017a, 2017b, 2017c, Park 2017)



# Kernel Machine Kids vs. Deep Learning Kids

- Fantastic Four in Deep Learning

Yann Lecun

Facebook AI Director  
Professor @NYU

Geoffrey Hinton

Fellow @ Google  
Professor @U of Toronto

Yoshua Bengio

Head of MILA

Andrew Ng

Chief Scientist @Baidu  
Co-Founder of Coursera  
Professor @Stanford Univ.



# Kernel Machine Kids vs. Deep Learning Kids

- The Three Musketeers in Kernel Machine

Vladimir Vapnik

Professor @RHUL

Book: Statistical Learning Theory

Bernhard Scholkopf

Director of Intelligent Systems

@Max Planck Institute

Book: Learning with Kernels

Alexander J. Smola

Professor @CMU

Book: Advances in Kernel Methods



BIG DATA

Facebook's AI team hires Vladimir Vapnik, father of the popular support vector machine algorithm

JORDAN NOVET @JORDANNOVET NOVEMBER 25, 2014 1:23 PM



# HOT Kids vs. BTS Kids



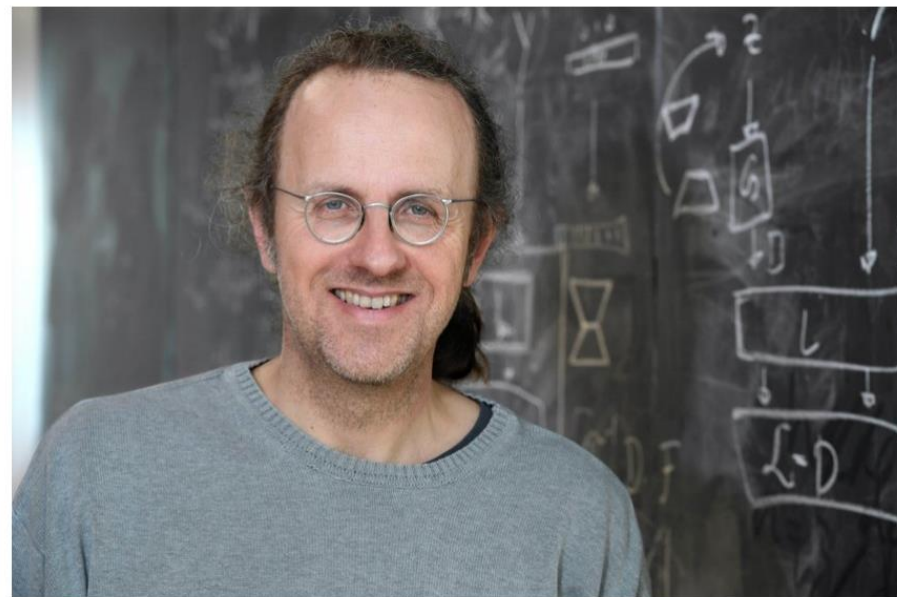
# Kernel Machine → Deep Learning

## Körber Prize 2019 for Bernhard Schölkopf

This year, the scientific distinction with the highest prize money in Germany goes to the pioneer of artificial intelligence

SEPTEMBER 13, 2019

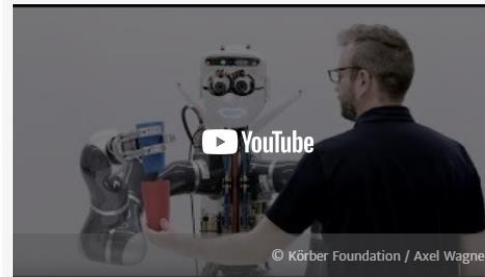
Bernhard Schölkopf, Director at the Max Planck Institute for Intelligent Systems in Tübingen, is honoured with the Körber Prize for European Science 2019. The Körber Foundation awards the prize to honour the computer scientist's contributions to machine learning, which today supplies one of the most important methods of Artificial Intelligence (AI). The Körber Prize includes prize money of one million Euros.



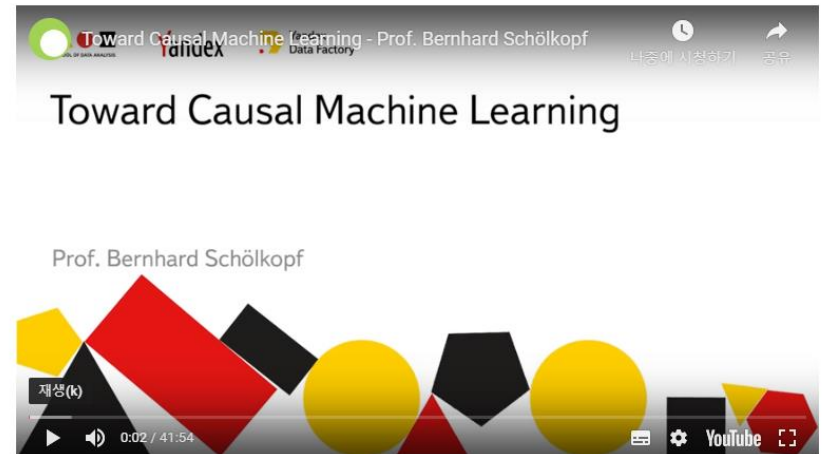
A pioneer of Artificial Intelligence: Bernhard Schölkopf receives the 2019 Körber Prize for European Science.  
© David Ausserhofer

<https://www.mpg.de/13645470/schoelkopf-koerber-prize>

## Causal relationships in data



## Teaching robots how to learn



[https://www.youtube.com/watch?time\\_continue=2&v=ooeRlw3U2zU](https://www.youtube.com/watch?time_continue=2&v=ooeRlw3U2zU)



# Kernel Machine → Deep Learning

AWS Startups Blog

## Alex Smola Showcases the Breadth of AWS's Machine Learning Capabilities at Collision 2018

by Michelle Kung | on 07 MAY 2018 | in Events | Permalink | Share



<https://aws.amazon.com/ko/blogs/startups/alex-smola-aws-machine-learning-collision-conference-new-orleans/>

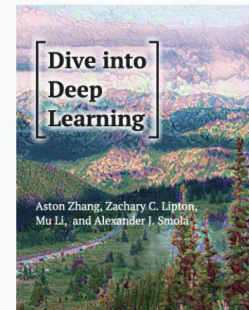
훗날 이 말을 한 당사자인 이진영이 은퇴 후 인터뷰에서 밝히길 야잘잘의 진짜 속뜻은 '야구를 잘하는 사람이 잘하지만 그걸 이겨내기 위해선 자신과 같은 길을 가는 경쟁자들을 어떻게 해야 이길 수 있는지 고민하고 노력하는 것'라고 밝혔다. 그러니까 재능 말고도 노력도 뒷받침해야 한다는 이야기

Dive into Deep Learning

- Preface
- Installation
- 1. Introduction
- 2. The Preliminaries: A Crashcourse
- 3. Linear Neural Networks
- 4. Multilayer Perceptrons
- 5. Deep Learning Computation
- 6. Convolutional Neural Networks
- 7. Modern Convolutional Networks
- 8. Recurrent Neural Networks
- 9. Attention Mechanism
- 10. Optimization Algorithms
- 11. Computational Performance
- 12. Computer Vision
- 13. Natural Language Processing
- 14. Generative Adversarial Networks
- 15. Appendix
- References

Dive into Deep Learning

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### Dive into Deep Learning

An interactive deep learning book with code, math, and discussions

A new version based on Numpy API is at <http://numpy.d2l.ai>

The contents are under revision

### Announcements

- [Stay tuned]** To keep track of the latest updates, please follow D2L's [open-source project](#).
- [Chinese version]** The Chinese version is the [best seller](#) of new books in "Computers and Internet" at the largest Chinese online bookstore.
- [Teaching]** Slides, Jupyter notebooks, assignments, and videos of the Berkeley course can be found at the [syllabus page](#).



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Mu Li

Amazon Principal Scientist  
CMU Ph.D.



Alex J. Smola

Amazon VP/Distinguished  
Scientist  
TU Berlin Ph.D.

<https://www.d2l.ai/>



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