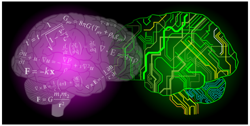
Physics And ML

Lec IV: Some Philosophical Aspects



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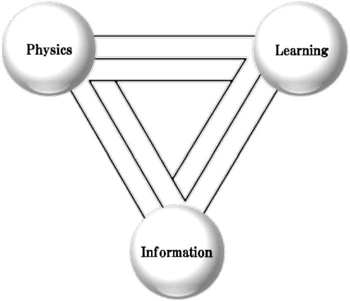
Physics and ML

- Physics and ML both deal with modeling and prediction
- Techniques and methods of machine learning are applicable to a large number of physics problems
- Physics could contribute to ML research
- In there more fundamental connection?

Physics-Information-ML



Information is the bridge between Physics and ML

Physics and Information

- Maximum Entropy Principle approch to Statistical Physics [1] ,[2]
- The relation of Shanon Entropy:

$$S = -\sum_i p_i \log p_i$$

- and the Gibbs Entropy:

$$S = k_B \sum_i p_i \log p_i$$

[1] Information Theory and Statistical Mechanics, E. T. Jaynes, Phys. Rev. 106, 620 –1957

[2] Information Theory and Statistical Mechanics II, E. T. Jaynes, Phys. Rev. 108, 171 – 1957

MaxEnt Principle

- Shanon Entropy: quantifies the statistical uncertainty about the value of x, from a probability distribution $p(x)$.
- **Principle of Maximum Entropy**: A physical system should be described by the probability distribution with the largest entropy subject to certain constraints
- **optimization** problem:

$$\mathcal{L}[p] = -S_p + \sum_i \lambda_i \left(\langle f_i \rangle_{\text{obs}} - \int \mathrm{d}\mathbf{x} f_i(\mathbf{x}) p(\mathbf{x}) \right) + \gamma \left(1 - \int \mathrm{d}\mathbf{x} p(\mathbf{x}) \right)$$

- i.e. Average energy $\Rightarrow$ Boltzmann distribution

From statistical mechanics to machine learning

- **Bayesian inference** provides a set of principles and procedures for learning from data and for describing uncertainty
- Learning that an unlikely event has occurred is more informative than learning that a likely event has occurred
- The goal of the **training** procedure is to use the available training data to fit parameters of probability distribution.
- The relative entropy?

$$D_{\mathrm{KL}}(P \| Q) = \sum_{x \in \mathcal{X}} P(x) \log \left(\frac{P(x)}{Q(x)} \right)$$

What is a physical law?

- The Whole Process:
  1. Information from nature
  2. (Complicated) process of analysis by the physicist (intelligence)
  3. Making Models
  4. Prediction of new Phenomena
- In Brief: Data$\Rightarrow$Training (intelligence) $\Rightarrow$ Predictions
- All Physics Problem are inverse problem
- How data is presented to make scientific explorations?
- The philosophy of science?

Statistic and Science Progress

- Does the statistic based on Frequentist or Bayesian approach?
- Probability and The Logic of Science [1]

[1] E. T. Jaynes, Probability Theory: The Logic of Science. Cambridge University Press, 2003

Some Fundamental Challenges In ML

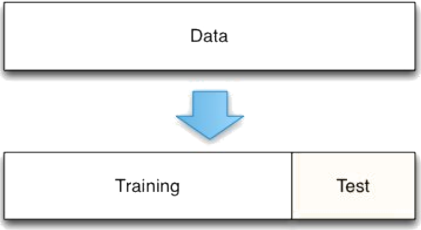
1. Overfitting and Underfitting
2. Bias-Variance Dilemma
3. No Free Lunch Theorems

The Prediction in ML

- New Data $\{x_{new}, y_{new}\}$

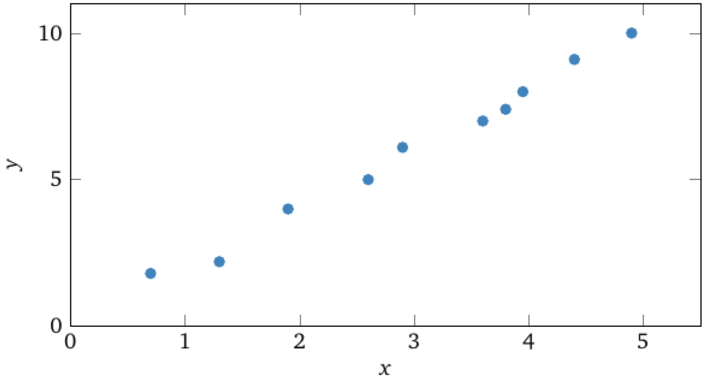
$$y_{new} = f(x_{new})?$$

- Training and Test Split:



- The value of the loss function in unseen data?
- The model is selected based on this behavior?

The Underfitting and Overfitting



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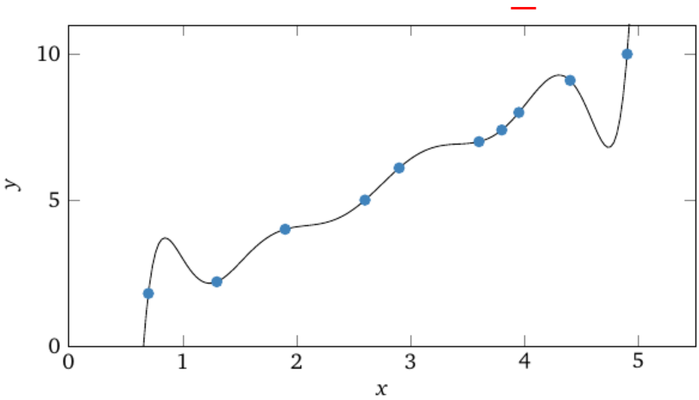
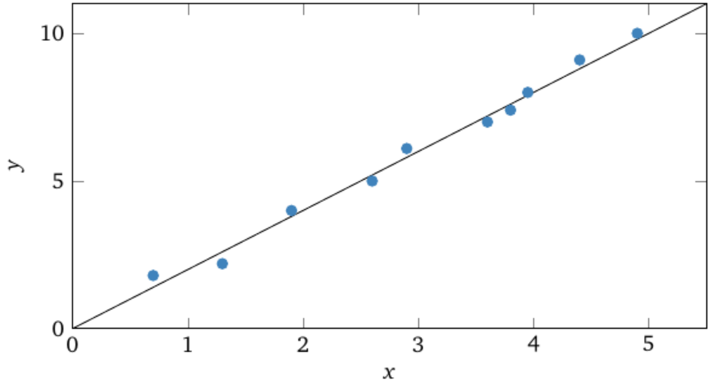
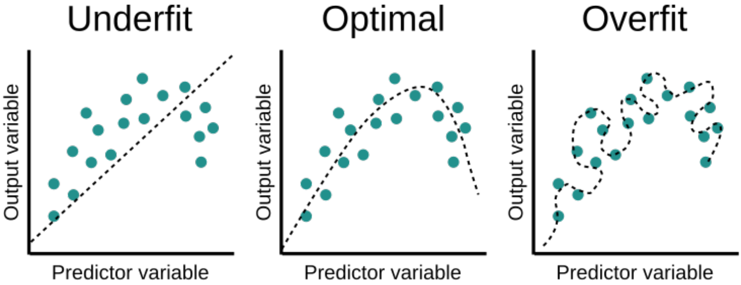


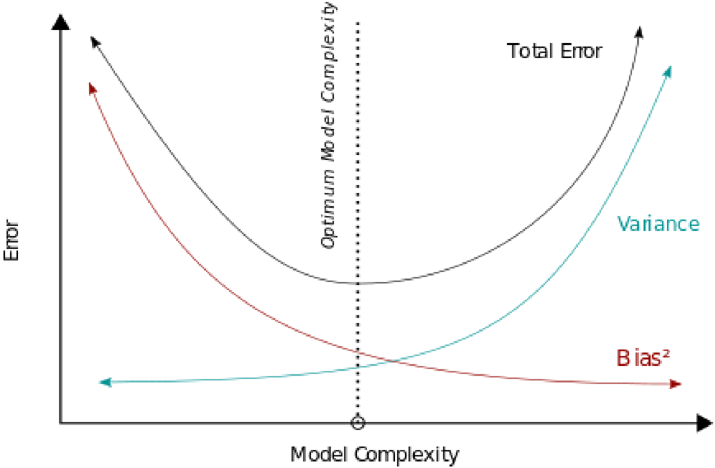
The Underfitting and Overfitting



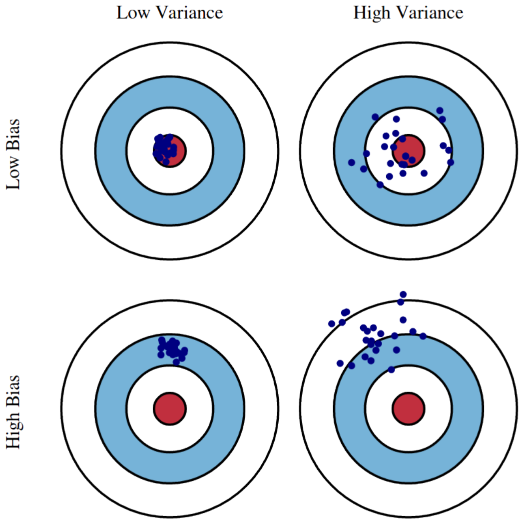
The Underfitting and Overfitting



BIAS—VARIANCE



BIAS—VARIANCE



BIAS–VARIANCE PROBLEM

- The Bias: error that comes from the potentially wrong **prior assumptions** in the model
- The variance : error that comes from the model's sensitivity to small variations
- Not possible to simultaneously decrease bias and variance error beyond training set

BIAS—VARIANCE PROBLEM

- In complex model with over-fitting: high variance, The model **memorizes**,
- Fails to correctly apply new real-world data (False learning)
- Every machine learning problem has a different point at which the bias-variance tradeoff is optimized
- There is no super-algorithm that can solve every machine learning problem better than every other algorithm.

The No Free Lunch Theorem[1,2]

- *There is no such a thing as a free lunch*
- Average over all possible machine-learning problems, all learning algorithms are equivalent
- no machine learning algorithm is universally any better than any other.
- the kinds of probability distributions we encounter in real-world applications
- we must design our machine learning algorithms to perform well on a specific task

[1] Wolpert, D.H., Macready, W.G. (1997)

[2] Wolpert, David (1996), , Neural Computation, pp. 1341–1390

No free Lunch Theorem

- Every machine learning algorithm makes **prior assumptions** about the relationship between the features and target variables for a machine learning problem.
- An algorithm may perform very well for one problem, but that gives us no reason to believe it will do just as well on a different problem where the same assumptions may not work.
- we cannot apply a conclusion about a particular set of observations to a more general set of observations

The problem of induction[1]

- Does we deduce scientific theories by **Induction**?
- The black swans case
- We cannot apply a conclusion about a particular set of observations to a more general set of observations
- knowledge is limited to the information (memorizing)?
- laws of physics $\Rightarrow$ **uniformity of nature?**

[1] The Stanford Encyclopedia of Philosophy, The Problem of Induction, (2018).

Why Physics And AI work?[1, 2]

- Wigner: "The unreasonable effectiveness of mathematics in the natural sciences"?
- Why physicist's crude experience leads to such accurate and predictive theories?
- The No Free Lunch Theorem: When you average over all possible machine-learning problems, all learning algorithms are equivalent
- Sparsity in Physics: Locality, Symmetry, ...
- Sparsity in AI?

[1] arXiv:2104.00008 , D. A. Roberts
[2] arXiv:1608.08225 , H. W. Lin , M. Tegmark , D. Rolnick

Effective Description

- No free lunch$\rightarrow$ Sparsity
- Locality, Symmetry, Typicality , $\Rightarrow$ Effective theories
- Effective description of the world
- No fundamental theory $\Rightarrow$ all theories must be effective

ML added to physics

- Traditionally, scientific research has revolved around theory and experiment
- Refines it using experimental data and analyses it to make new predictions.
- **Data-driven approaches to science**
- An existing theory is not required (No explicit rules)
- Machine learning algorithm can be used to analyses a scientific problem using data alone.

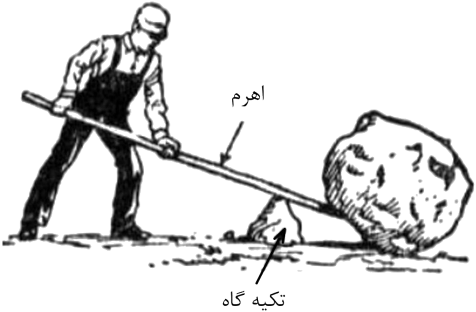
The End of Theory?

- The End of Theory: The Data Deluge Makes the Scientific Method Obsolete[1]

[1] https://www.wired.com/2008/06/pb-theory/, Chris Anderson

Learn The nature?

- Do we always need the **explicit** form of laws?
- From our elementary school physics:



- Almost all skill are **Learning** type
- Why not science?

Learn The Laws?

- Why The Laws?
- There is a vast landscape of equally consistent theories
- The Space of Laws parameterized by Coupling constants, masses, ...
- Universe learn its laws in a multiverse space?[1]

[1] arXiv:2104.03902, S. Alexander, W. J. Cunningham, J. Lanier, **L. Smolin**, S. Stanojevic, M. W. Toomey, D. Wecker

Machine Learning the Data in Publication

HEP-TH[1]

- ArXiv: A lot of information about physics
- Harness the information for Physics itself?
- Investigate the language of theoretical physics
- Idea generating machines

$$\texttt{'holography'} + \texttt{'quantum'} + \texttt{'string'} + \texttt{'ads'} = \texttt{'extremal-black-hole'}$$

$$\texttt{'black-hole'} + \texttt{'holographic'} = \texttt{'thermodynamics'}$$

[1] arXiv:1807.00735, Y. He, V. Jejjala, B. D. Nelson

The laws and Brains

- How Do we understand the laws?
- conciseness being?
- Is the black box of brain works like NN?
- Does the brains trained over the evolution process?

Physics ML Groups

1. Institute for Artificial Intelligence and Fundamental Interactions (IAIFI)[1]
   - collaboration of both physics and AI researchers
2. The Center for Brains, Minds & Machines (CBMM)[2]
   - Max Tegmark groub [3]

[1] iaifi.org
[2] cbmm.mit.edu
[3] super-ms.mit.edu/physics-ai.html

Conclusion

- Many concepts in ML and physics are similar
- Using ML for a large variety of problems in physics
- Physics could help developments in ML
- Possible new directions in ML/Physics
- ML-Physics is still in its infancy
- ML in future seems to be in future an important ingredient of physical theories like algebra and differential equations