



Fundamentals of Machine Learning (III)

- Learn the sources of errors when you apply your ML model for new data
- Learn the gold standard: evaluate the performance of machine learning algorithms with cross validation

[https://www.sli.do/
#ML101](https://www.sli.do/#ML101)

汝為Ai人，不可不知Ai事



OpenAI has officially released 'o1' (internally known as Project Strawberry/Q*), its first AI model with advanced 'reasoning' capabilities.

The details:

- o1 uses **reinforcement learning** and **chain-of-thought** processing to "think" before responding, mimicking human problem-solving.
- It outperforms expert humans on PhD-level science questions and ranks in the 89th percentile for competitive programming.
- The model also solved 83% of International Mathematics Olympiad qualifying exam problems, compared to GPT-4o's 13%.

Why it matters: OpenAI o1 is better than expert humans **on PhD-level science questions**. Its enhanced reasoning capabilities by "thinking" before responding will not only lead to more accurate AI responses, but opens up an entirely new world of real-world use cases for complex problems in science, coding, math, and more.

IQ Test Results

Score reflects average of last 7 tests given

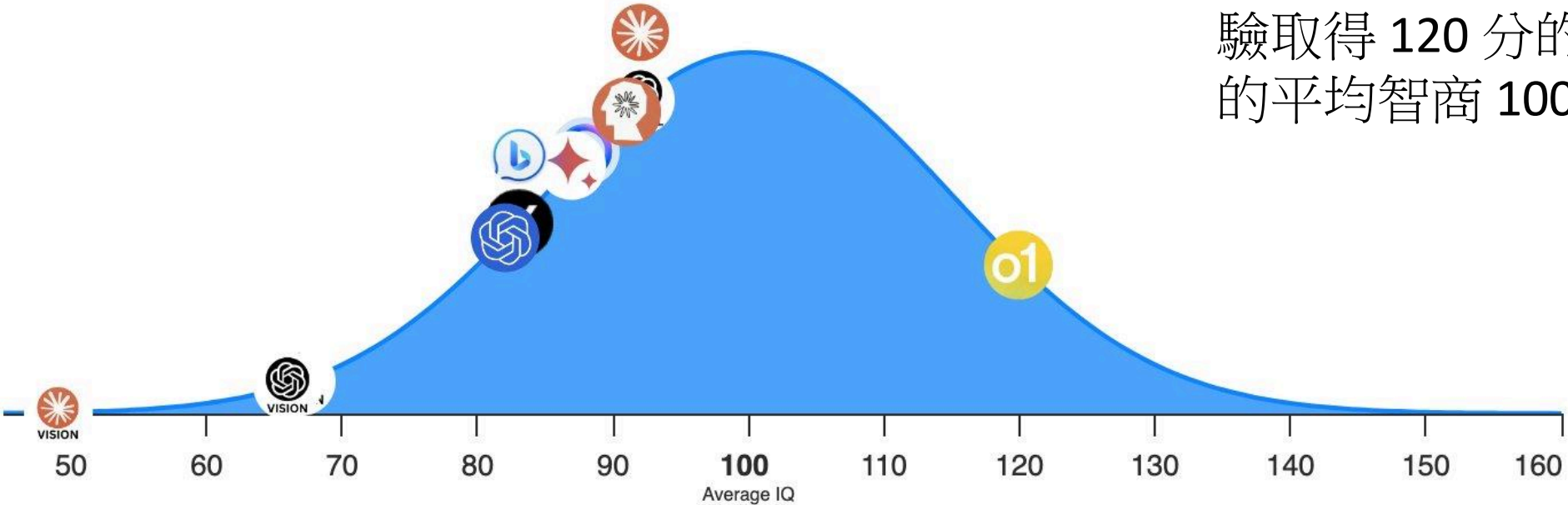
Reset

Show Offline Test

Show Mensa Norway

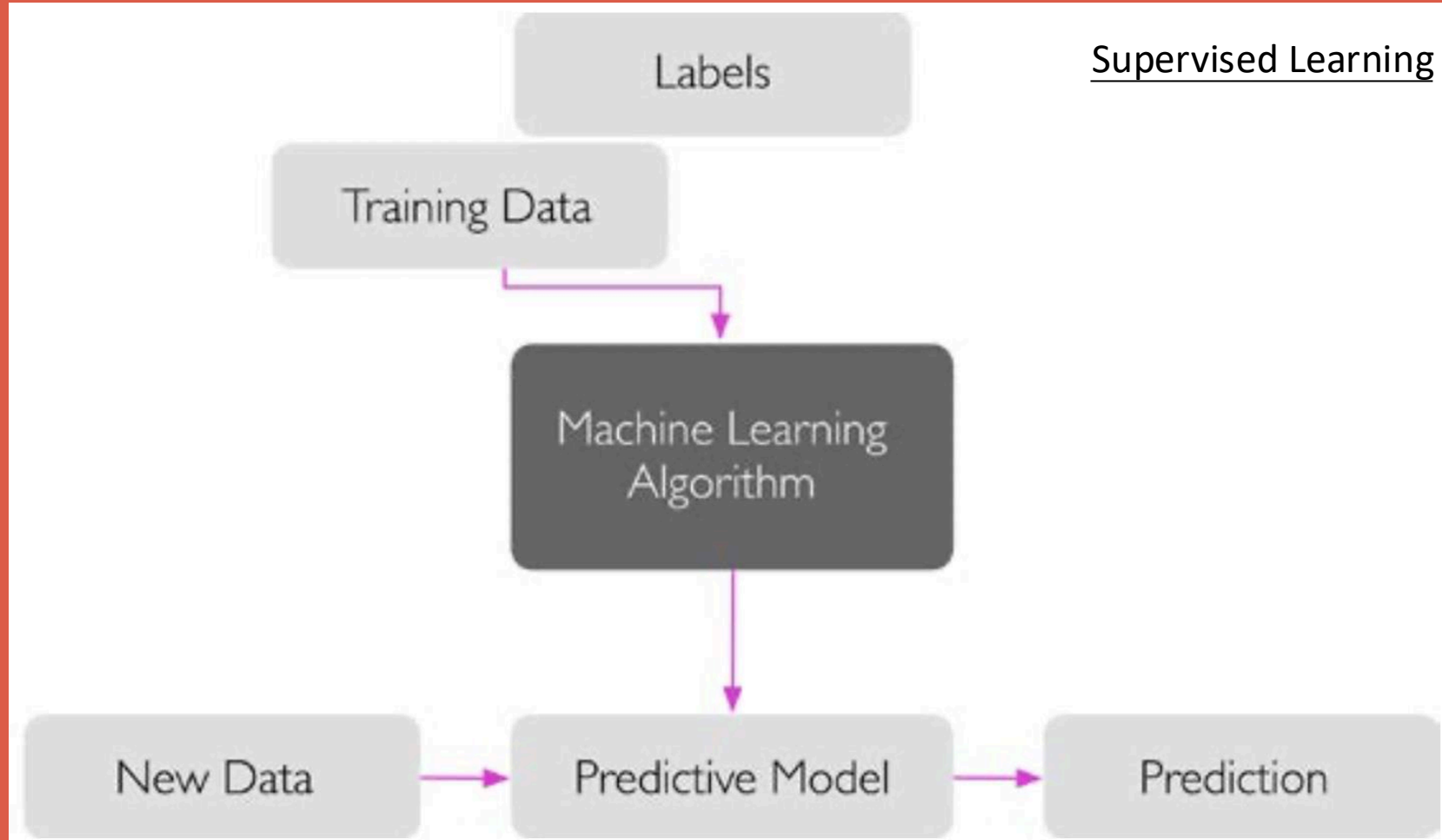


OpenAI 最新的模型 o1 在智力測驗取得 120 分的成績，超越人類的平均智商 100

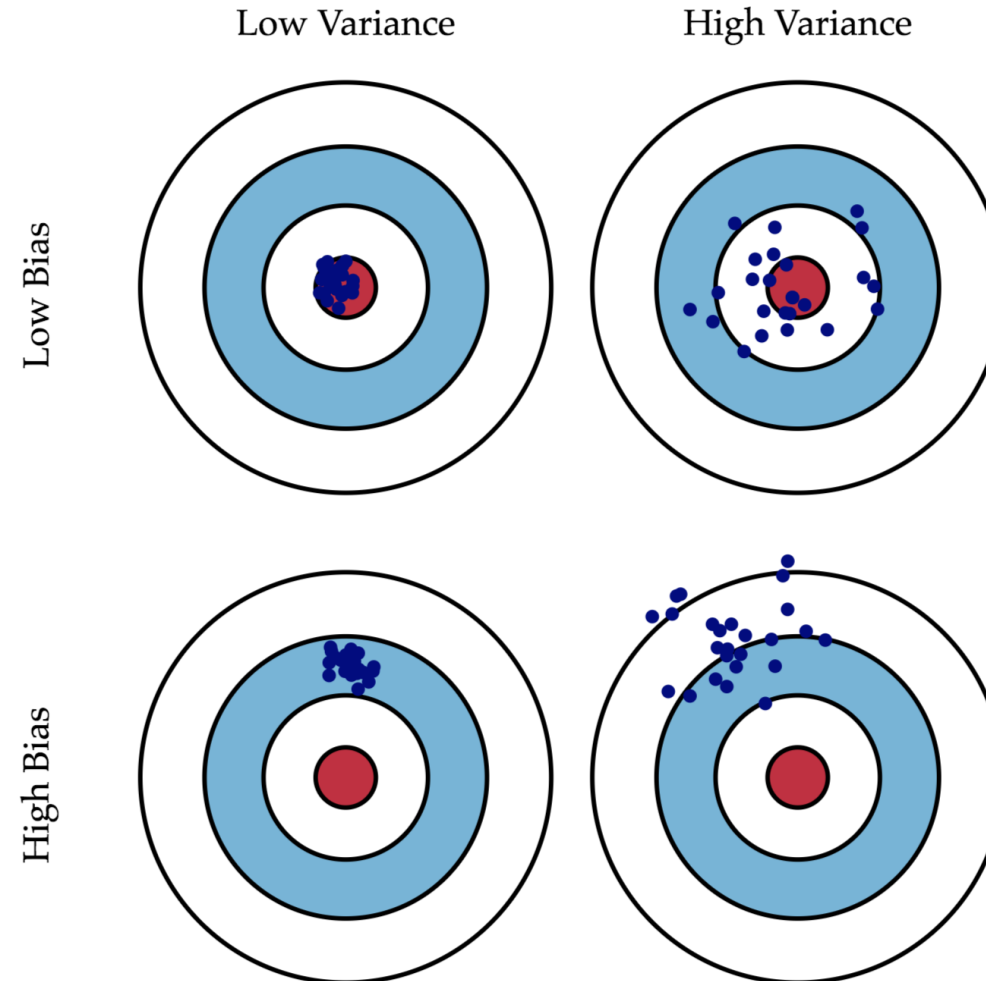


- | | | |
|--------------------------|-----------------|------------------------|
| OpenAI o1 preview | Llama-3.1 | Grok-2 |
| Gemini Advanced (Vision) | Gemini Advanced | GPT4 Omni (Vision) |
| GPT4 Omni | ChatGPT-4 | Bing Copilot |
| Claude-3.5 Sonnet | Claude-3 Opus | Claude-3 Opus (Vision) |

Learn the sources of errors when you apply your ML model for new data

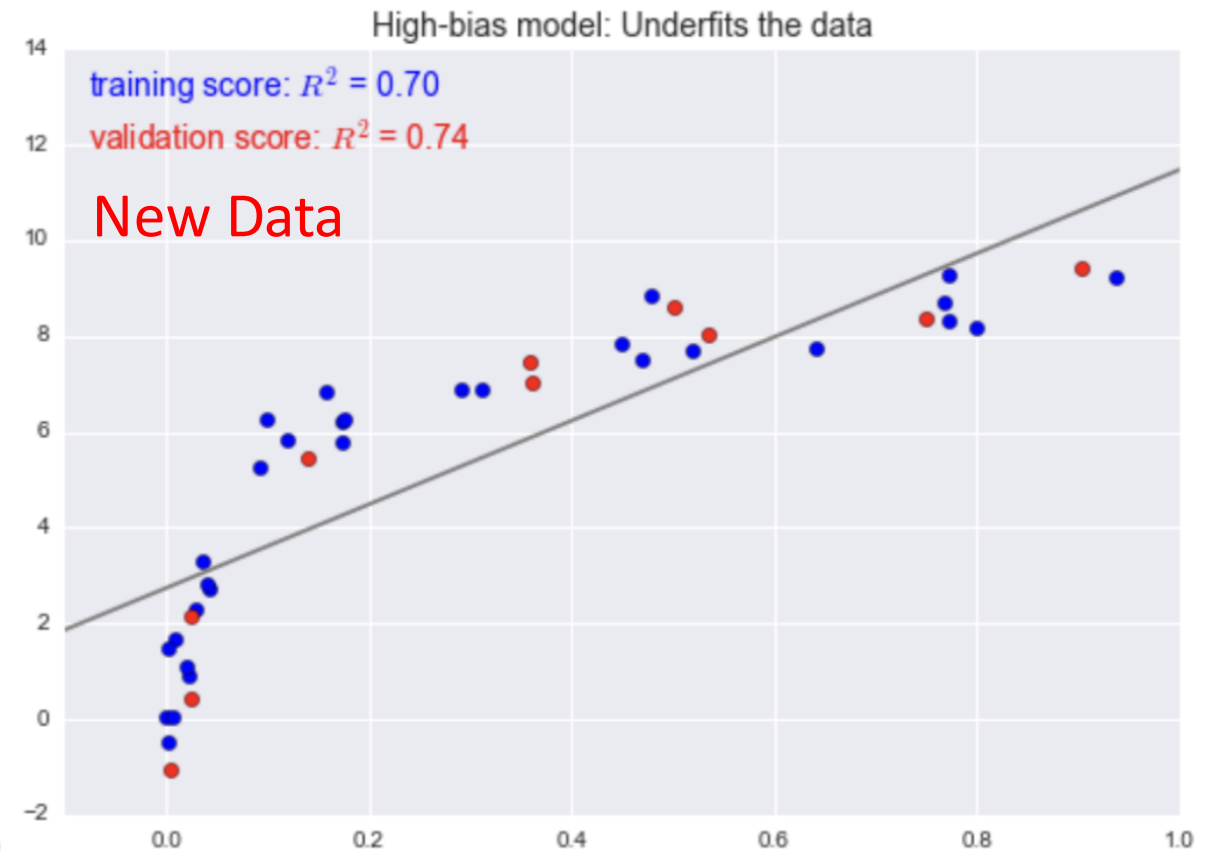
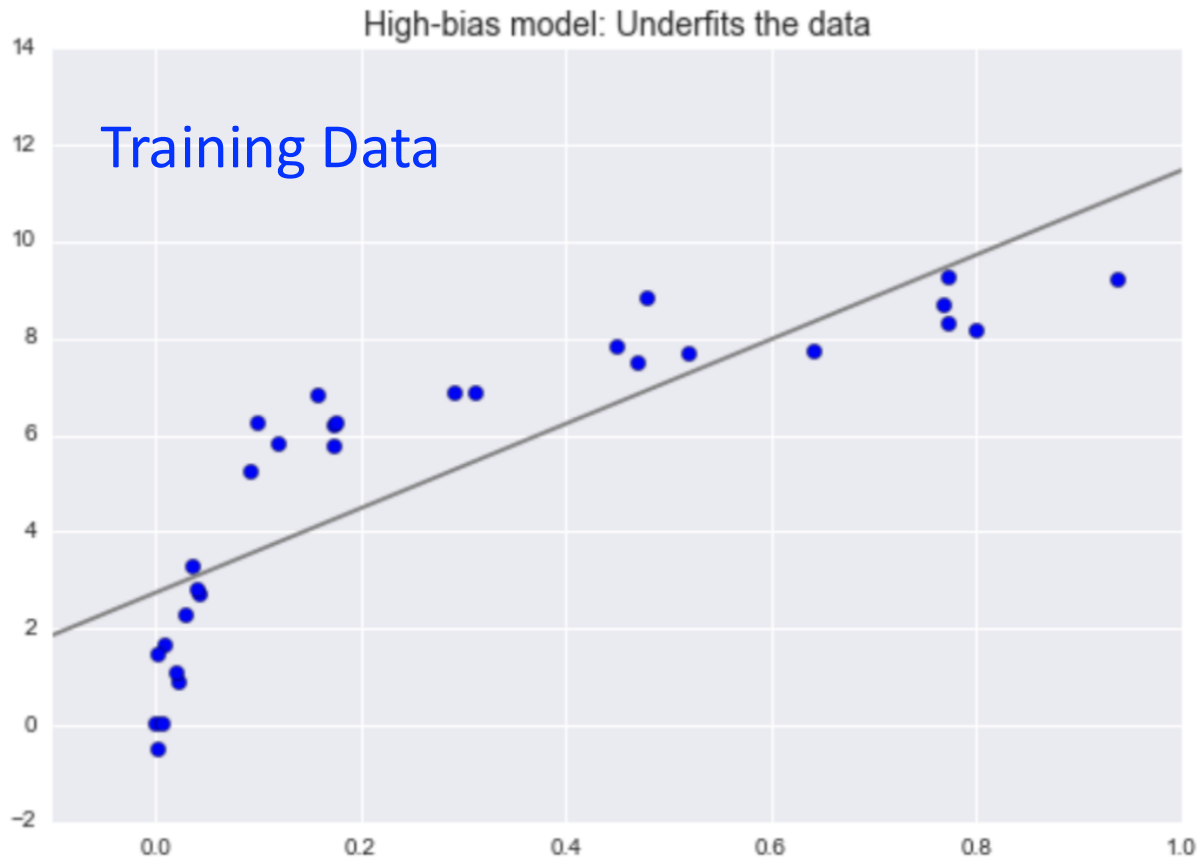


Bias and **variance** are two major sources of errors that prevent supervised learning algorithms from generalizing beyond their training set



Intuitive **High Bias** Example: low-order polynomial fitting (**underfit**)

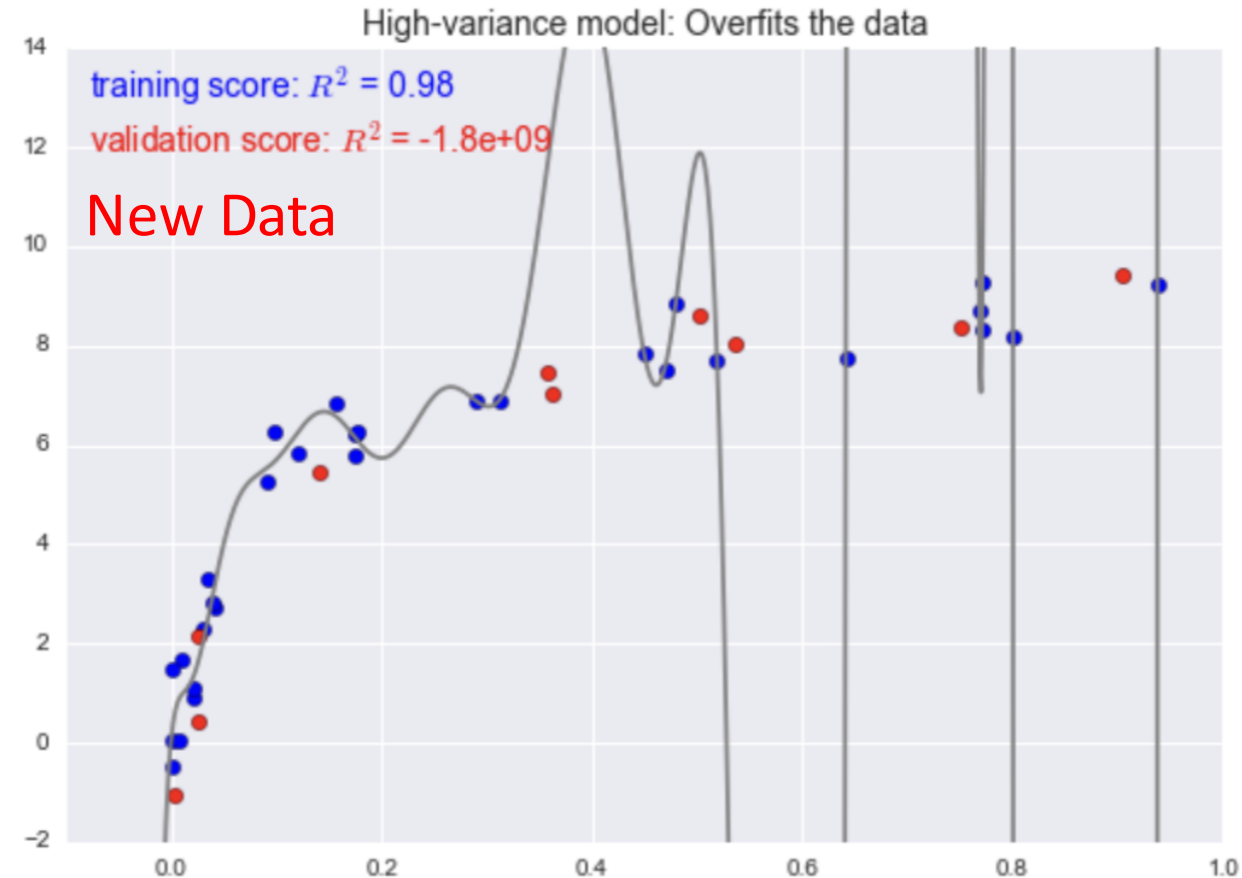
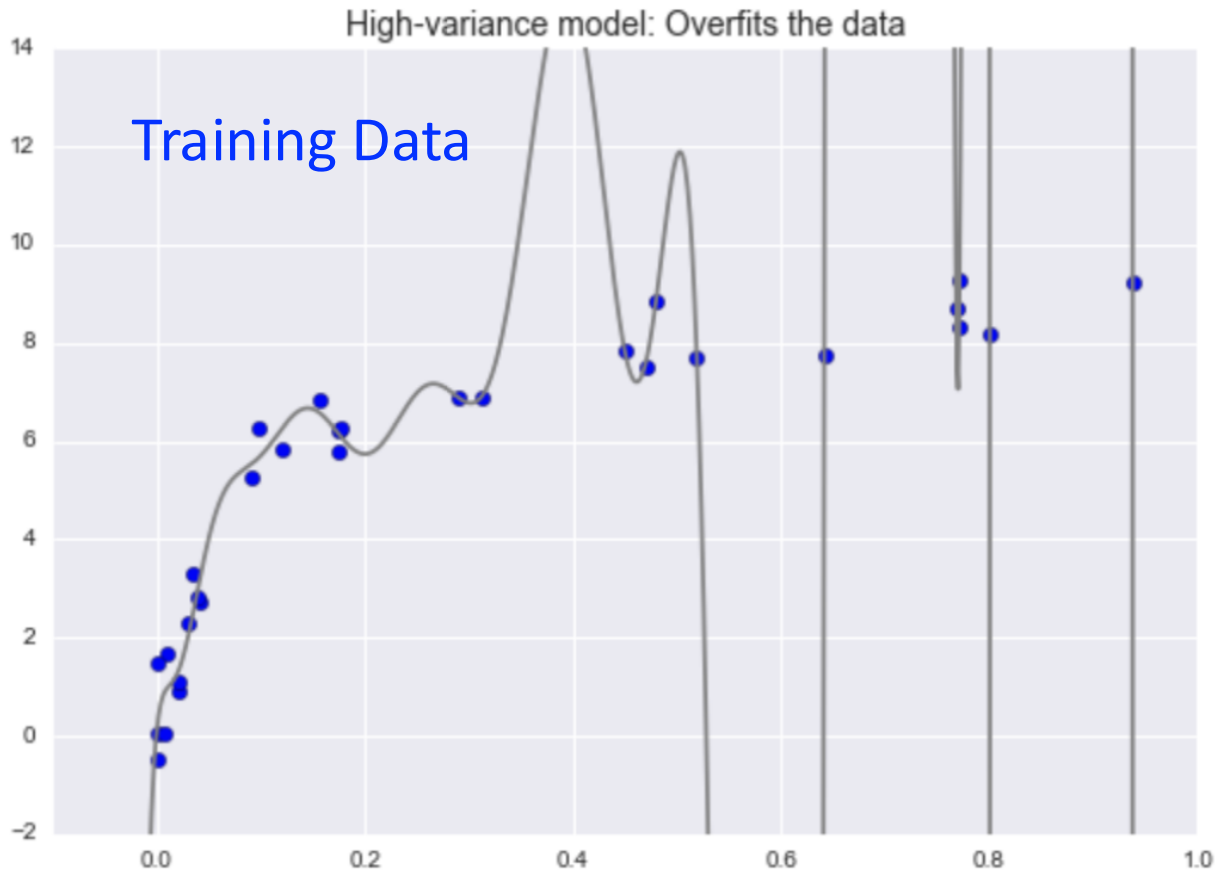
$$p = 1$$



$R^2 = 1$ indicates a perfect match, $R^2 = 0$ indicates the model does no better than simply taking the mean of the data, and negative values mean even worse models.

Intuitive **High Variance** Example: high-order polynomial fitting (**overfit**)

$$p = 20$$

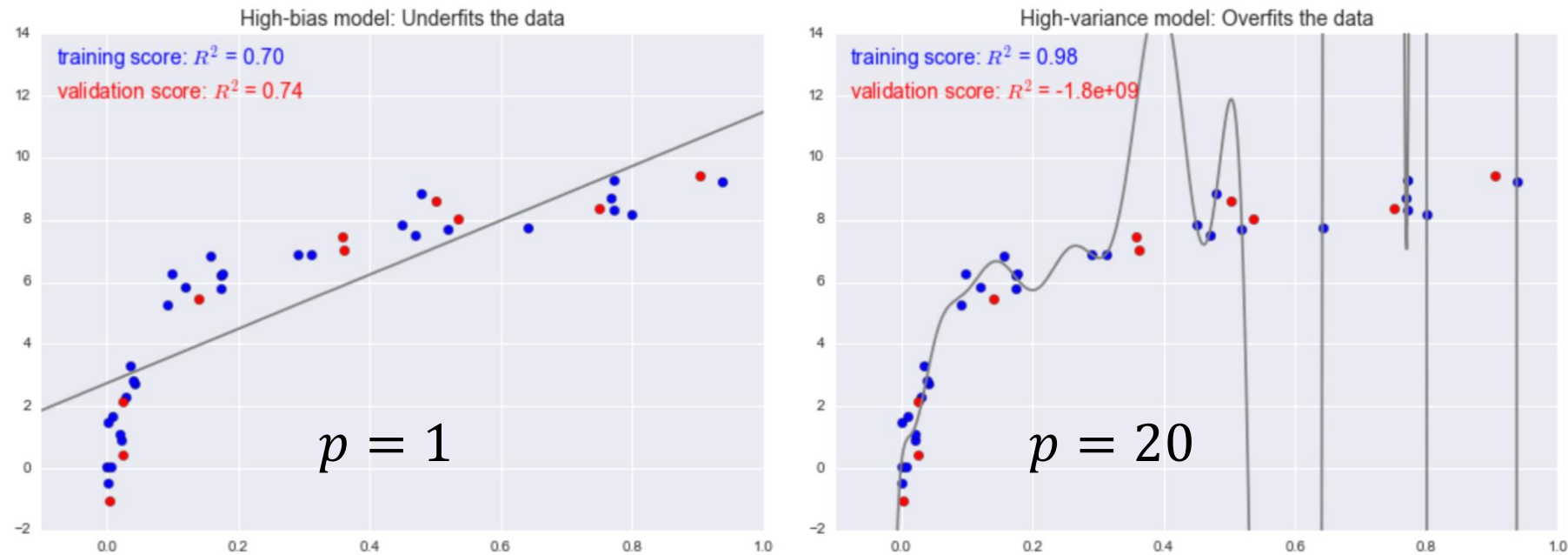


$R^2 = 1$ indicates a perfect match, $R^2 = 0$ indicates the model does no better than simply taking the mean of the data, and negative values mean even worse models.

Fun Time: 假設你正在開發一個機器學習模型來預測房價。你的模型在訓練資料上的預測誤差非常小，但在測試資料上的誤差卻非常大。這種現象最有可能是由哪種問題導致的？

- (1) 高偏差 (High bias)
- (2) 高變異 (High variance)
- (3) 低偏差 (Low bias)
- (4) 低變異 (Low variance)

“Best” ML Model: find the optimal trade-off between **bias** and **variance**



- “Human” search: let us work through the example and find the best model (best polynomial curve)
- See `Bias_var_intuitive_example.ipynb`



Summary

Bias and variance tradeoff: an intuitive example

- **High bias** model (low order polynomial) tends underfit the data.
- **High variance** model (high order polynomial) tends overfit the data.
- "The best ML model" is about **finding a sweet spot in the tradeoff between bias and variance**.
- The optimal model will generally depend **on the size** of training data.

Bias and variance: theoretical minimum and example

- The phrase “theoretical minimum” is taken from a very successful book series written by Leonard Susskind, a great physicist at Stanford University.
- “Theoretical minimum” means just the minimum theories and equations you need to know in order to proceed to the next level.
- See Bias_Variance.pdf

Summary

Learn the sources of errors when you apply your learning model for new data

- **Bias** and **variance** are two major sources of errors that prevent supervised learning algorithms from generalizing beyond their training set.
- Fundamentally, the question of "the best ML model" is about **finding a sweet spot in the tradeoff between bias and variance**.
- The optimal model will generally depend **on the size** of training data.
- For general cases, it is not possible to explicitly compute bias and error; we rely on **the validation curve** and **the learning curve** to help us spot them.

Evaluate the performance of machine learning algorithms with cross validation

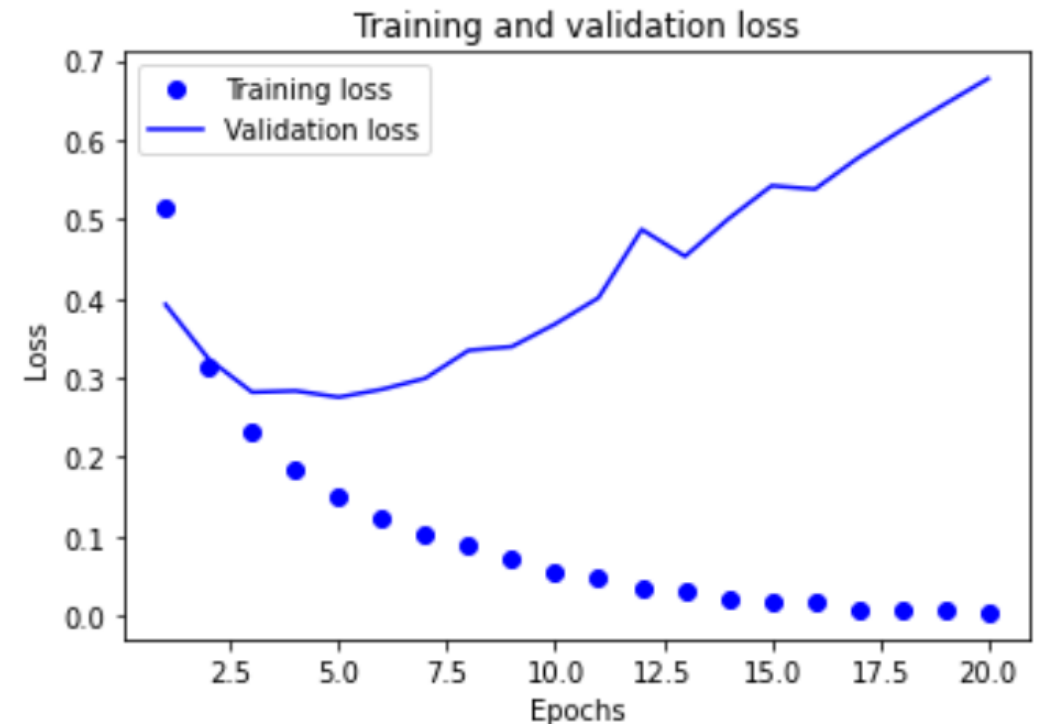
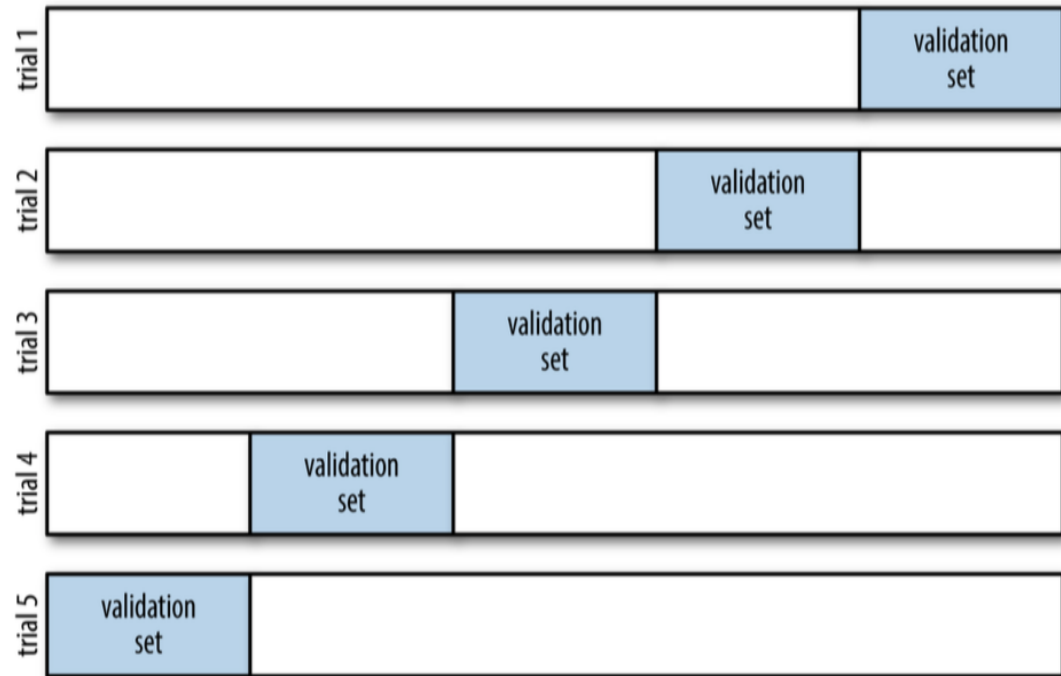
Fun Time: 在開發模型時你只會有一組千辛萬苦得到的資料，通常我們會把一部分資料用來訓練模型，一部分資料用來評估模型面對新資料的表現。

If we split data into train and test data (say 50/50). Use train data to fit the model and use test data to evaluate performance of your algorithm. What is the potential problem of this approach?

- 1. waste of data for training**
- 2. waste of data for testing**
- 3. all of the above**
- 4. none of the above.**

Machine Learning vs. Deep Learning: Performance Assessment

- K-fold cross validation is a gold standard in classical machine learning to evaluate performance but rarely used in deep learning (computational prohibited)
- Gold standard in deep learning is the validation curve.

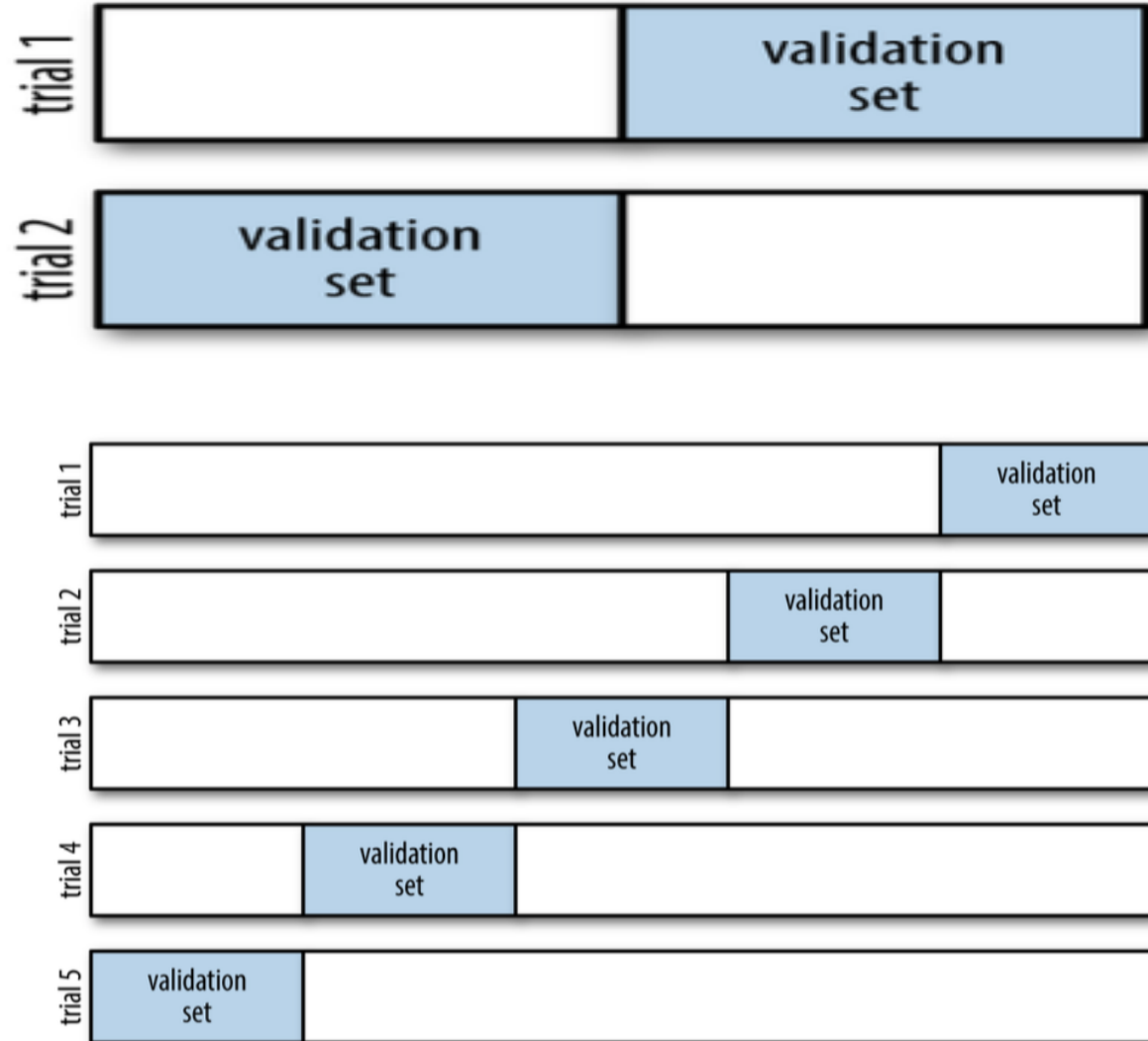


Evaluate the performance of machine learning algorithms with cross validation



Cross_validation.ipynb

- K-fold cross validation is a gold standard in classical machine learning to evaluate performance



Fundamentals of Machine Learning: Summary

- Machine learning: use data to compute **hypothesis g** that approximate unknown **target f** .
- In practice, **learning algorithm \mathcal{A}** takes training examples **\mathcal{D}** and **hypothesis set \mathcal{H}** to get **final hypothesis g** .
- Learning is only feasible in a **probabilistic** way and we can predict something useful outside the training set \mathcal{D} using only \mathcal{D} .
- **Scikit-Learn** and **Keras** (now part of TensorFlow) are mostly widely used ML software frameworks by ML professionals.
- From 2016 to 2020, the entire machine learning industry has been dominated by **deep learning** and **gradient boosted trees**.
- Specifically, gradient boosted trees is used for problems where structured data is available, whereas deep learning is used for perceptual problems such as image classification.

Fundamentals of Machine Learning: Summary

- **Bias** and **variance** are two major sources of errors that prevent supervised learning algorithms from generalizing beyond their training set
- Fundamentally, the question of "the best ML model" is about finding a sweet spot in the tradeoff between bias and variance.
- For general cases, it is not possible to explicitly compute bias and error; we rely on the **validation curve** and the **learning curve** to help us spot them.
- **K-fold cross validation** (3, 5, 10) is a gold standard in classical machine learning to evaluate model performance but rarely used in deep learning (computational prohibited).
- Gold standard in deep learning is the **validation curve**.