Guided Tour of Machine Learning in Finance

The No Free Lunch Theorem

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The Bias-Variance Tradeoff

$$\mathbb{E}\left[\left(y-\hat{f}(\boldsymbol{x})\right)^2\right]=(bias)^2+variance+noise$$

- **Bias-variance tradeoff:**
  - <u>Complex models</u> (more features) tend to have <u>low bias</u> and <u>high variance</u>
  - <u>Simple models</u> (less features) tend to have <u>high bias</u> and <u>low variance</u>
- Important to control **model complexity** to have an optimal tradeoff!

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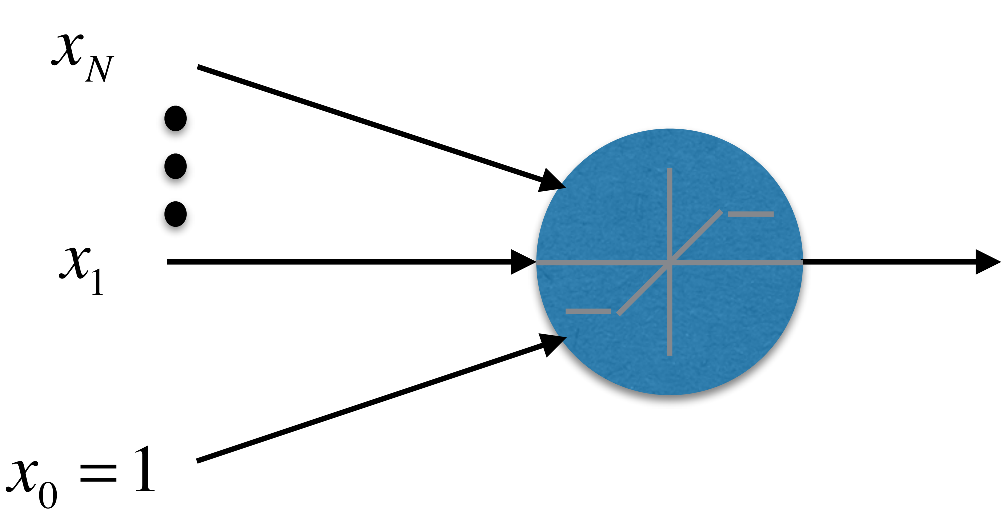

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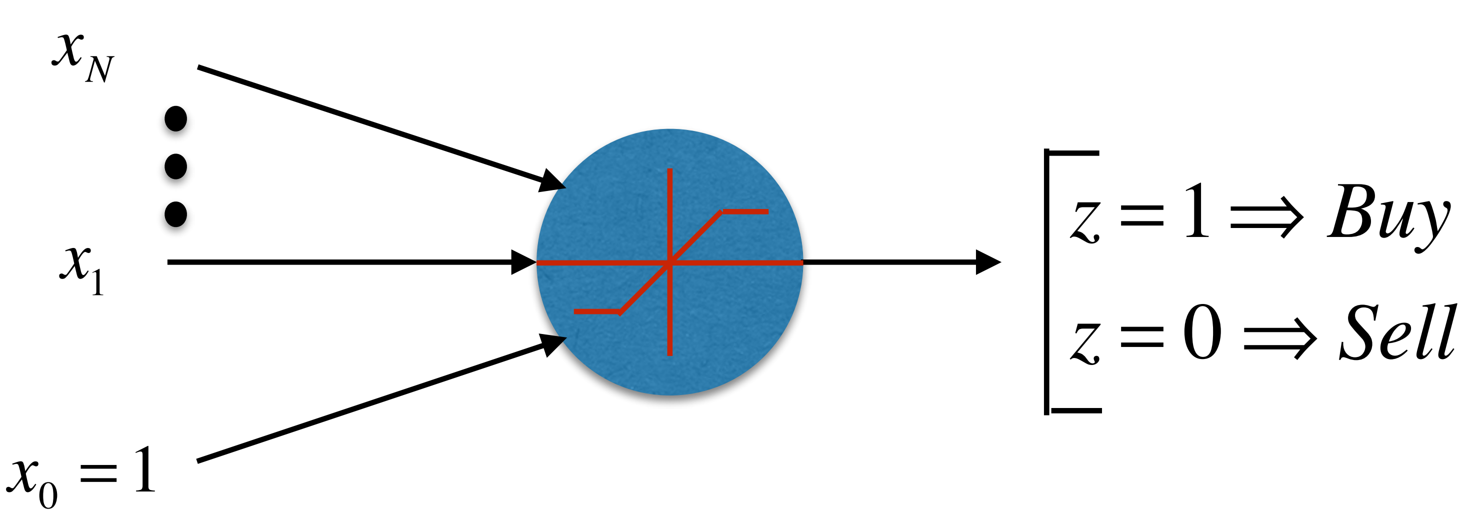

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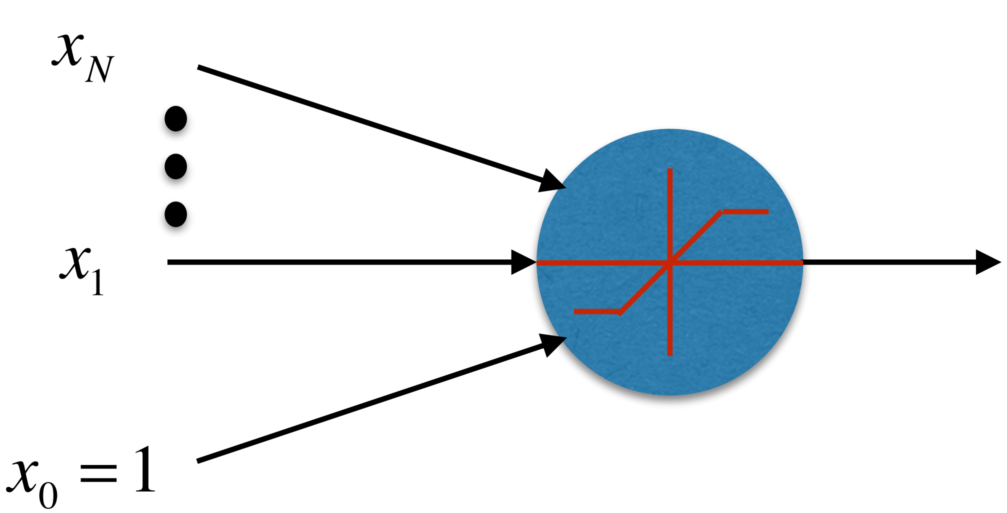

$$\begin{cases} z = 1 \Rightarrow Buy \\ z = 0 \Rightarrow Sell \end{cases}$$

Adjustable parameters

$$E.g.: \sigma(z = \sum_{i=0}^{N} \theta_n x_n) = 1/(1+\exp(-z))$$

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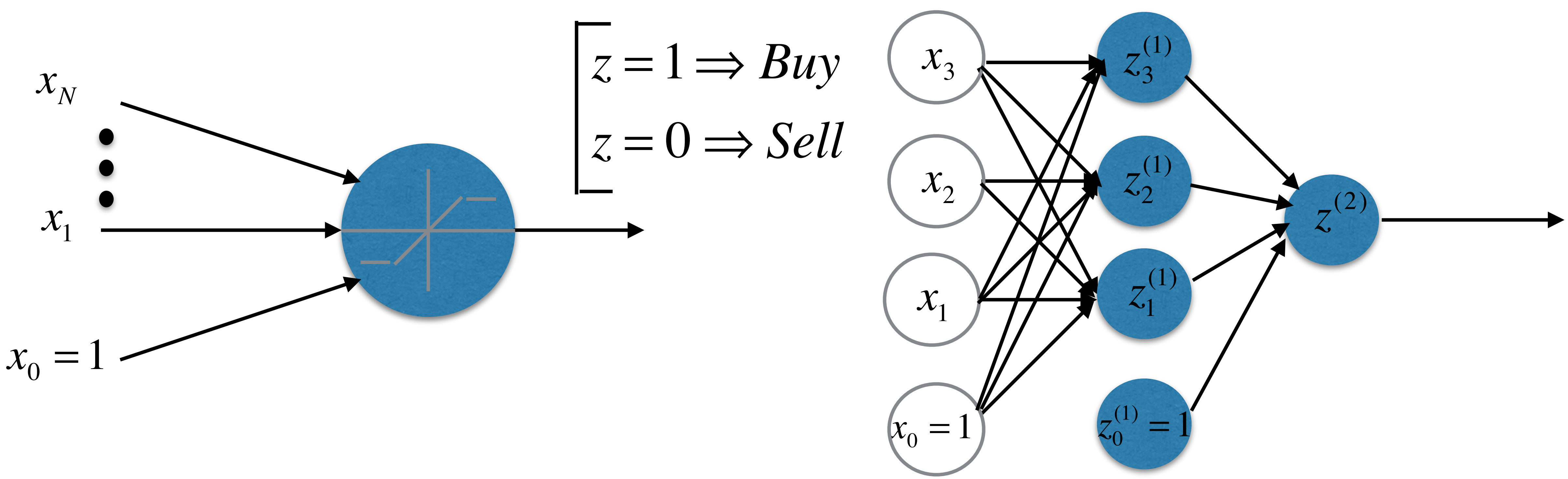

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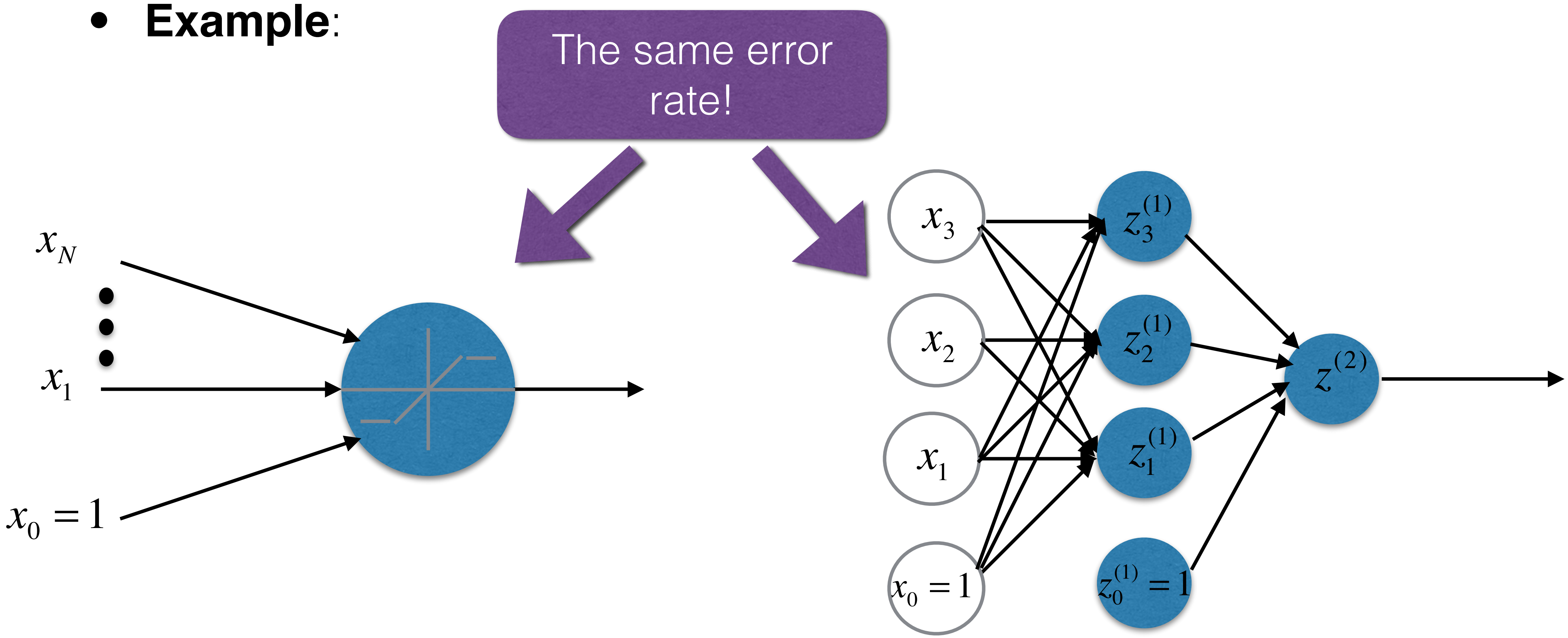

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- **A** p**ractical remedies**:
  - ✦ Look for ML algorithms that perform best on certain <u>classes of domains</u> (characterized by a data-generating distribution p_{data}).