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- How do we know a restaurant we visited for the first time is actually good?
- How do we know we didn’t just happen to get their best dish on a good night?

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- For tractability, we impose a strong assumption on the distribution of ϵ

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- The agent updates his beliefs to $\mathbb{E}_{t+1}[a_i]$ by incorporating new information in S_{it}
- This process repeats itself in each period where S_{it} is received

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Assume WLOG that $\mathbb{E}(a_i) = 0$ and $\mathbb{E}(\varepsilon_{it}) = 0$ for all t

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Then we can decompose the variance of the signal S_{it}

$$\begin{aligned}\mathbb{V}(S_{it}) &= \mathbb{V}(a_i) + \mathbb{V}(\varepsilon_{it}) \\ &= \sigma_a^2 + \sigma_\varepsilon^2\end{aligned}$$

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This ratio measures the quality of the signal (bigger is better)

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This is used in common formulas for updating beliefs