

Lecture 3

Probabilistic Reliability

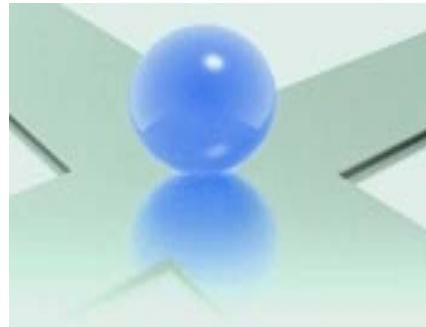
with

Info-Gap Uncertainty

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1 *Probabilistic Reliability in Engineering with Info-Gaps*

§ **Source:**

Yakov Ben-Haim, *Info-Gap Economics:
An Operational Introduction*, Palgrave, 2010.

1.1 The Problem: Uncertainties

§ The problem:

- **Fat tails:**
 - Extreme outcomes too frequent.
 - High percentiles under-estimated.
-

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- Extreme outcomes too frequent.
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- **Past vs future:**

- Processes vary in time.
 - Data are revised.
 - Shackle-Popper indeterminism.

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§ The problem:

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- Extreme outcomes too frequent.
- High percentiles under-estimated.

- **Past vs future:**

- Processes vary in time.
- Data are revised.
- Shackle-Popper indeterminism.

- **Joint probabilities:**

- Uncertain common-mode failures.
- Uncertain correlations.

§ Two foci of uncertainty:

- Statistical fluctuations:
 - Randomness, “noise”.
 - Estimation uncertainty.
-

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- Knightian uncertainty:
 - Surprises.
 - Structural changes.
 - Historical data used to predict future.

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§ Info-gap theory to manage

Knightian uncertainty.

§ Outline:

- **Discrete system with 2 sub-units:**
 - Reliability.
 - Redundancy.
 - Uncertain correlation.
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- Reliability.
- Redundancy.
- Uncertain correlation.

- Origin of fat tails:

Parameter uncertainty.

-

§ Outline:

- Discrete system with 2 sub-units:
 - Reliability.
 - Redundancy.
 - Uncertain correlation.
- Origin of fat tails:
Parameter uncertainty.
- Quantile uncertainty.
 - Fat tails.
 - Thin tails.

1.2 Reliability, Redundancy, Uncertain Correlation

§ System with 2 sub-units:

- Serial: **both units essential.**
- Parallel: **either unit sufficient.**

§

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- Parallel: either unit sufficient.

§ Probabilities of failure:

- F_i = marginal prob of failure of unit i .
- F_{12} = prob of joint failure.

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- Serial: both units essential.
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- F_i = marginal prob of failure of unit i .
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§ Probabilities of system failure:

- **Serial:** $F_s = F_1 + F_2 - F_{12}$.
(Explain: Venn)
- **Parallel:** $F_p = F_{12}$

§ Example.

- **Estimates:** $\widetilde{F}_i = 0.01$. $\widetilde{F}_{12} = 0.0001$
- **Serial:** $F_s = 0.0199$. **Not too good.**
- **Parallel:** $F_p = 0.0001$. **Not too bad.**

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- **Serial:** $F_s = 0.0199$. **Not too good.**
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§ Problem:

Estimates of F_i and F_{12} uncertain.

$$|F_i - \widetilde{F}_i| \leq h, \quad i = 1, 2$$

$$|F_{12} - \widetilde{F}_{12}| \leq h$$

Horizon of uncertainty, h , is unknown.

§ Info-gap model:

$$\mathcal{U}(h) = \{ F_1, F_2, F_{12} : F_1 \geq 0, F_2 \geq 0, F_{12} \geq 0,$$

$$F_{12} \leq \min[F_1, F_2].$$

$$F_1 + F_2 - F_{12} \leq 1.$$

$$|F_i - \bar{F}_i| \leq h, i = 1, 2.$$

$$|F_{12} - \bar{F}_{12}| \leq h \}, h \geq 0$$

•

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- **Contraction:** $\mathcal{U}(0) = \{\bar{F}_1, \bar{F}_2, \bar{F}_{12}\}.$

-

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- **Contraction:** $\mathcal{U}(0) = \{\bar{F}_1, \bar{F}_2, \bar{F}_{12}\}.$

- **Nesting:** $h < h' \implies \mathcal{U}(h) \subseteq \mathcal{U}(h').$

- **Family of nested sets.**

-

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- **Contraction:** $\mathcal{U}(0) = \{\bar{F}_1, \bar{F}_2, \bar{F}_{12}\}.$
- **Nesting:** $h < h' \implies \mathcal{U}(h) \subseteq \mathcal{U}(h').$
- **Family of nested sets.**
- **No known worst case.**

§ Performance requirements:

- Acceptable failure probabilities:

- **Serial:** $F_s \leq F_{cs}$

- **Parallel:** $F_p \leq F_{cp}$

§

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- Maximum tolerable uncertainty.
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- Max horizon of uncertainty at which failure probability acceptable.
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§ Performance requirements:

- Acceptable failure probabilities:

 - Serial: $F_s \leq F_{cs}$

 - Parallel: $F_p \leq F_{cp}$

§ Robustness:

- Maximum tolerable uncertainty.
- Max horizon of uncertainty at which failure probability acceptable.
- Serial and parallel robustness:

$$\widehat{h}_s(F_{cs}) = \max \left\{ h : \left(\max_{F_i, F_{12} \in \mathcal{U}(h)} F_s \right) \leq F_{cs} \right\}$$

$$\widehat{h}_p(F_{cp}) = \max \left\{ h : \left(\max_{F_i, F_{12} \in \mathcal{U}(h)} F_p \right) \leq F_{cp} \right\}$$

§ Derive parallel robustness.

§ Ramp function:

$$\bar{r}(x) = \begin{cases} 0 & x < 0 \\ x & 0 \leq x \leq 1 \\ 1 & 1 < x \end{cases} \quad (1)$$

§ Inverse of robustness:

$$\mu(h) = \max_{F_i, F_{12} \in \mathcal{U}(h)} F_p, \quad F_p = F_{12} \quad (2)$$

§

§ Derive parallel robustness.

§ Ramp function:

$$\bar{r}(x) = \begin{cases} 0 & x < 0 \\ x & 0 \leq x \leq 1 \\ 1 & 1 < x \end{cases} \quad (3)$$

§ Inverse of robustness:

$$\mu(h) = \max_{F_i, F_{12} \in \mathcal{U}(h)} F_p, \quad F_p = F_{12} \quad (4)$$

§ Uncertainty and robustness:

$$|F_{12} - \bar{F}_{12}| \leq h \implies \mu(h) = \bar{r}(\bar{F}_{12} + h) \quad (5)$$

$$\mu(h) \leq F_{cp} \implies \hat{h}_p(F_{cp}) = F_{cp} - \bar{F}_{12} \quad (6)$$

or zero if negative.

§ Derive serial robustness.

§ Inverse of robustness:

$$\mu(h) = \max_{F_i, F_{12} \in \mathcal{U}(h)} F_s, \quad F_s = F_1 + F_2 - F_{12} \quad (7)$$

§

§ Derive serial robustness.

§ Inverse of robustness:

$$\mu(h) = \max_{F_i, F_{12} \in \mathcal{U}(h)} F_s, \quad F_s = F_1 + F_2 - F_{12} \quad (8)$$

§ Uncertainty and inverse robustness:

$$\begin{aligned} F_i, F_{12} &\in \mathcal{U}(h) \implies \\ \mu(h) &= \bar{r} [\bar{r}(\bar{F}_1 + h) + \bar{r}(\bar{F}_2 + h) - \bar{r}(\bar{F}_{12} - h)] \end{aligned} \quad (9)$$

§

§ Derive serial robustness.

§ Inverse of robustness:

$$\mu(h) = \max_{F_i, F_{12} \in \mathcal{U}(h)} F_s, \quad F_s = F_1 + F_2 - F_{12} \quad (10)$$

§ Uncertainty and inverse robustness:

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§ Robustness:

- Plot h vs. $\mu(h)$.
- No need to invert $\mu(h)$.

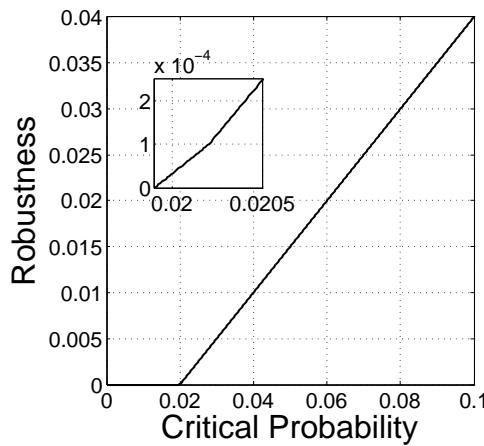


Figure 1: **Serial robustness.** $\tilde{F}_i = 0.01$, $\tilde{F}_{12} = 0.0001$.

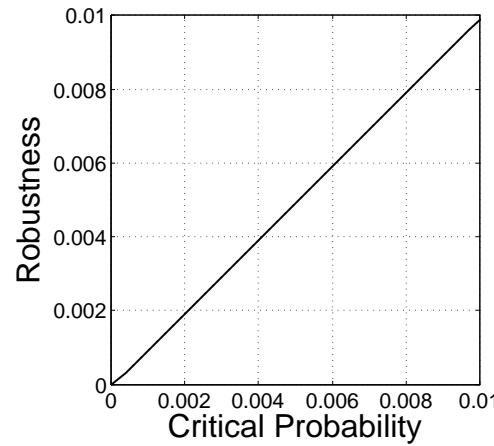


Figure 2: **Parallel robustness.** $\tilde{F}_i = 0.01$, $\tilde{F}_{12} = 0.0001$.

§ Trade-off: Robustness vs. critical probability

§

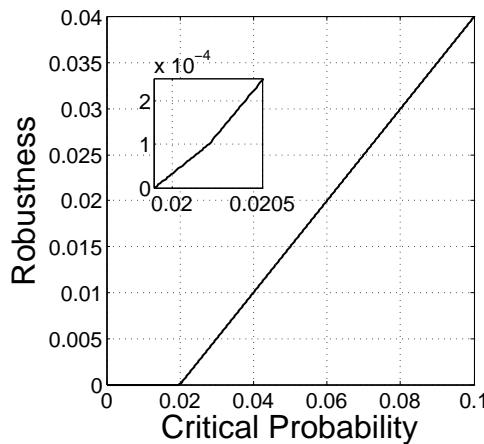


Figure 3: **Serial robustness.** $\tilde{F}_i = 0.01$, $\tilde{F}_{12} = 0.0001$.

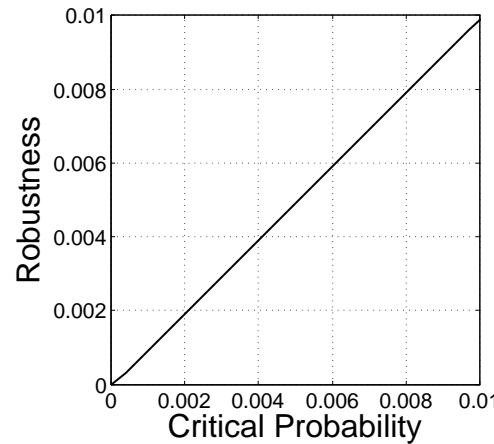


Figure 4: **Parallel robustness.** $\tilde{F}_i = 0.01$, $\tilde{F}_{12} = 0.0001$.

§ **Trade-off:** Robustness vs. critical probability

§ **Zeroing:** No robustness of estimated failure probability

§

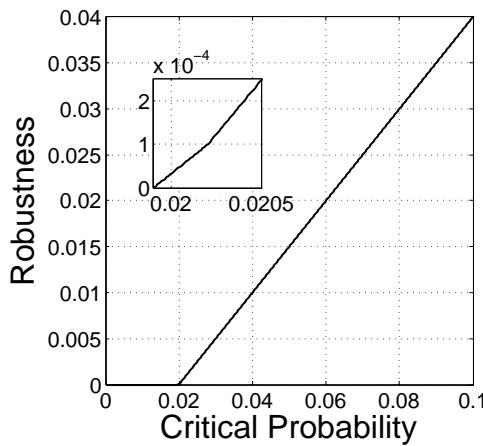


Figure 5: **Serial robustness.** $\tilde{F}_i = 0.01$, $\tilde{F}_{12} = 0.0001$.

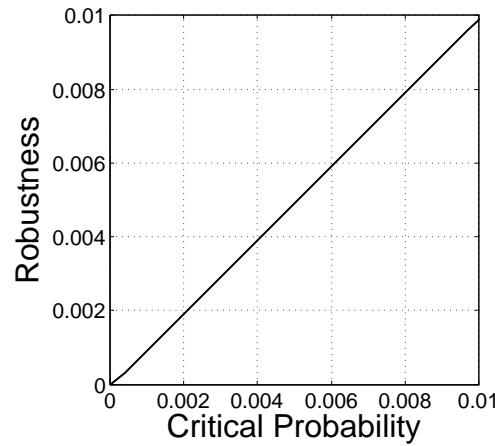


Figure 6: **Parallel robustness.** $\tilde{F}_i = 0.01$, $\tilde{F}_{12} = 0.0001$.

§ Trade-off: Robustness vs. critical probability

§ Zeroing: No robustness of estimated failure probability

§ High cost of rbs: large slope.

- **Serial:** $\Delta \hat{h} / \Delta F_{cs} = 0.5$.
- **Parallel:** $\Delta \hat{h} / \Delta F_{cp} = 1$.

§ Summary of Reliability, Redundancy, Uncertain Correlation: Analysis of uncertainty is essential.

1.3 Parameter Uncertainty and FAT Tails

§ Basic idea:

- Fat tails:
 - Tail decays slower than exponential.
 - Not all moments exist.
- Thin-tail pdf may have uncertain parameters.
- Total pdf may be fat tailed.

Example of Fat Tails

§ Exponential distribution of t .

- t is a random variable, e.g. lifetime:

$$f(t|\lambda) = \lambda e^{-\lambda t}, \quad t \geq 0 \quad (12)$$

- All moments of $t|\lambda$ exist.

§

Example of Fat Tails

§ Exponential distribution of t .

- t is a random variable, e.g. lifetime:

$$f(t|\lambda) = \lambda e^{-\lambda t}, \quad t \geq 0 \quad (13)$$

- All moments of $t|\lambda$ exist.

§ Gamma distribution of λ

- λ is uncertain.

E.g., mixture of populations.

$$\pi(\lambda) = \frac{\alpha}{\Gamma(k)} (\alpha \lambda)^{k-1} e^{-\alpha \lambda}, \quad \lambda \geq 0, \quad \underbrace{\alpha > 0, k > 0}_{\text{parameters}} \quad (14)$$

- All moments of λ exist.

§ What is marginal distribution of t ?

- $t|\lambda$ is **exponential** (thin).
- λ is **Gamma** (thin).
- t is **Pareto** (fat).
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- Define: $Y = 1 + \frac{T}{\alpha}$
- Y is **Pareto**: $f(y) = k \left(\frac{1}{y}\right)^{k+1}, \quad y \geq 1$
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§ What is marginal distribution of t ?

- $t|\lambda$ is exponential (thin).
- λ is Gamma (thin).
- t is Pareto (fat).
- Define: $Y = 1 + \frac{T}{\alpha}$
- Y is Pareto: $f(y) = k \left(\frac{1}{y}\right)^{k+1}, \quad y \geq 1$

- Mean and variance:

$$\begin{aligned} E(y) &= \frac{k}{k-1} \quad \text{if } k > 1 \\ \text{var}(y) &= \frac{k}{k-2} - \left(\frac{k}{k-1}\right)^2 \quad \text{if } k > 2 \end{aligned}$$

- Not all moments exist.
- Parameter uncertainty implies fat tails.

1.4 Quantile Uncertainty

§ Outcome, reward, r :

- Random variable.
- Large is better than small.

§

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- Random variable.
- Large is better than small.

§ Decision: Choose system: mean, variance.

§ Problem: Distribution uncertain.

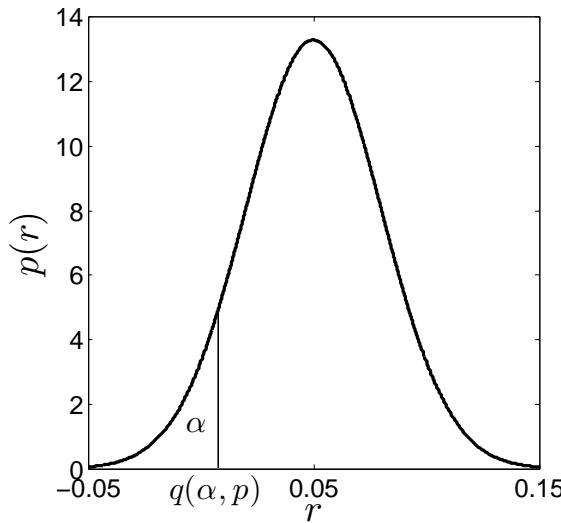


Figure 7: α quantile, $q(\alpha, p)$.

§ α Quantile, $q(\alpha, p)$:

$$\alpha = \int_{-\infty}^{q(\alpha, p)} p(r) dr \quad (15)$$

- α is probability of failure.
- $q(\alpha, p)$ is critical value of r .

§ Small quantile (far left) \iff high risk.

- α (e.g. = 0.05) is probability of loss $\geq |q(\alpha, p)|$.
- Suppose $q(\alpha, p)$ is very negative.
- Thus probability is α of very large loss.

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§ Performance requirement:

$$q(\alpha, p) \geq R_C \quad (16)$$

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- α (e.g. = 0.05) is probability of loss $\geq |q(\alpha, p)|$.
- Suppose $q(\alpha, p)$ is very negative.
- Thus probability is α of very large loss.

§ Performance requirement:

$$q(\alpha, p) \geq R_C \quad (17)$$

§ Problem:

- pdf of r highly uncertain.
- May have fat tails.
- Hence $q(\alpha, p)$ highly uncertain.

§ Question: Is the system reliable?

§ Info-gap model of uncertainty:

- $\tilde{p}(r)$ is **estimated pdf**; e.g. normal.
- Envelope-bound uncertainty:

$$|p(r) - \tilde{p}(r)| \leq g(r)h \quad (18)$$

§

§ Info-gap model of uncertainty:

- $\tilde{p}(r)$ is **estimated pdf**; e.g. normal.
- Envelope-bound uncertainty:

$$|p(r) - \tilde{p}(r)| \leq g(r)h \quad (19)$$

§ How to choose envelope?

- Engineering judgment.
- Dimensional analysis.
- Analogical reasoning.
- Assess “equivalent risk”.

§ Info-gap model of uncertainty:

- $\tilde{p}(r)$ is **estimated pdf**; e.g. normal.
- Envelope-bound uncertainty:

$$|p(r) - \tilde{p}(r)| \leq g(r)h \quad (20)$$

§ Example: $g(r)$ is “ $1/r^2$ ” on tails:

$$g(r) = \begin{cases} \frac{\tilde{p}(\mu - r_s)(\mu - r_s)^2}{r^2} & \text{if } r < \mu - r_s \\ \tilde{p}(r) & \text{if } |r - \mu| \leq r_s \\ \frac{\tilde{p}(\mu + r_s)(\mu + r_s)^2}{r^2} & \text{if } r > \mu + r_s \end{cases} \quad (21)$$

Mean and variance may be unbounded.

§ Robustness:

Max horizon of uncertainty at which loss is acceptable:

$$\hat{h}(\alpha, R_C) = \max \left\{ h : \left(\min_{p \in \mathcal{U}(h)} q(\alpha, p) \right) \geq R_C \right\} \quad (22)$$

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$$\hat{h}(\alpha, R_C) = \max \left\{ h : \left(\min_{p \in \mathcal{U}(h)} q(\alpha, p) \right) \geq R_C \right\} \quad (23)$$

§ Robustness depends on:

- Underlying design, e.g. μ, σ .
- Designated failure probability, α .
- Critical loss, R_C .

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§ Robustness:

Max horizon of uncertainty at which loss is acceptable:

$$\hat{h}(\alpha, R_C) = \max \left\{ h : \left(\min_{p \in \mathcal{U}(h)} q(\alpha, p) \right) \geq R_C \right\} \quad (24)$$

§ Robustness depends on:

- Underlying design, e.g. μ , σ .
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§ Robustness is a decision function:

- Satisfy requirements.
- Maximize robustness.
-

§ Robustness:

Max horizon of uncertainty at which loss is acceptable:

$$\hat{h}(\alpha, R_C) = \max \left\{ h : \left(\min_{p \in \mathcal{U}(h)} q(\alpha, p) \right) \geq R_C \right\} \quad (25)$$

§ Robustness depends on:

- Underlying design, e.g. μ , σ .
- Designated failure probability, α .
- Critical loss, R_C .

§ Robustness is a decision function:

- Satisfy requirements.
- Maximize robustness.
- **Don't** try to optimize the outcome (e.g. $q(\alpha, p)$).

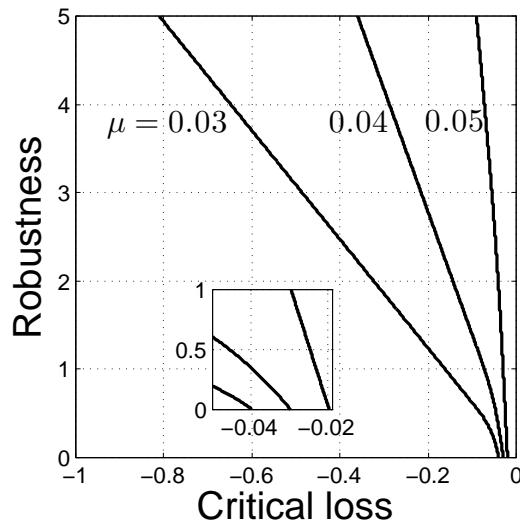


Figure 8: Robustness, \widehat{h} , vs. critical loss, R_C , for 3 values of μ . $\sigma = 0.03$.

§ Trade-off: robustness vs critical loss.

§

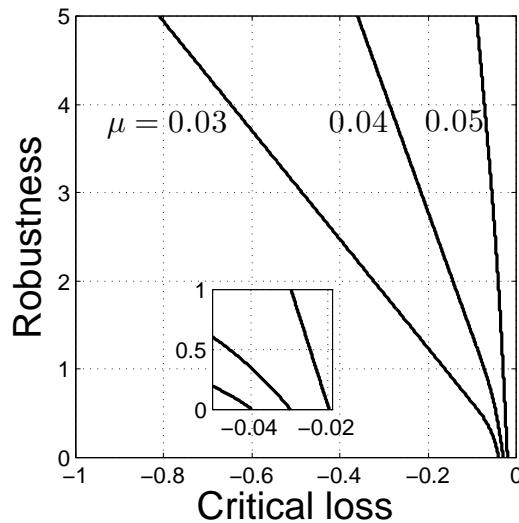


Figure 9: Robustness, \widehat{h} , vs. critical loss, R_C , for 3 values of μ . $\sigma = 0.03$.

§ **Trade-off:** robustness vs critical loss.

§ **Zeroing:** No robustness of estimated critical loss.

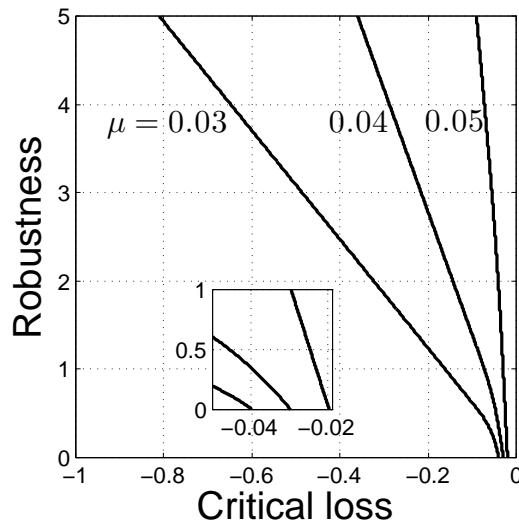


Figure 10: Robustness, \widehat{h} , vs. critical loss, R_C , for 3 values of μ . $\sigma = 0.03$.

§ Effects of increasing the mean:

- Shift to higher robustness.
-

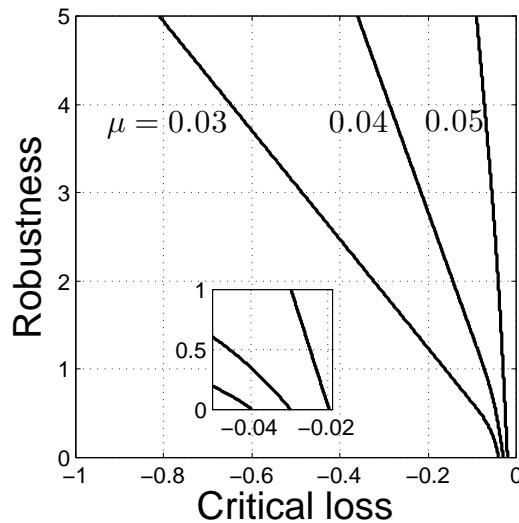


Figure 11: Robustness, \widehat{h} , vs. critical loss, R_C , for 3 values of μ . $\sigma = 0.03$.

§ Effects of increasing the mean:

- Shift to higher robustness.
- Increase slope: **reduce cost of rbs.**

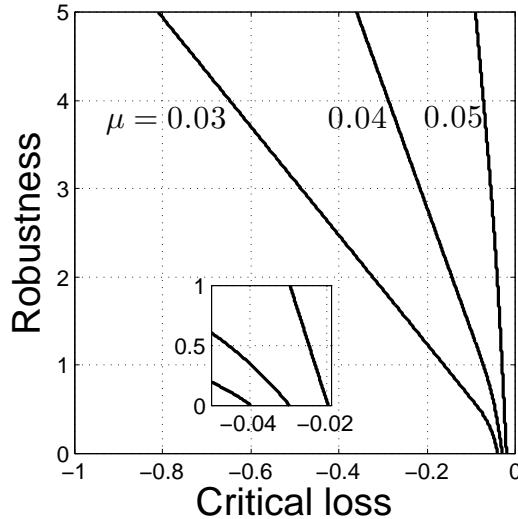


Figure 12: Robustness, \widehat{h} , vs. critical loss, R_C , for 3 values of μ . $\sigma = 0.03$.

§ Calibrating the robustness.

- Is robustness of 3 or 5 “large”?
- $\widehat{h} = 3$ means $3 \times$ tail is tolerable.
-

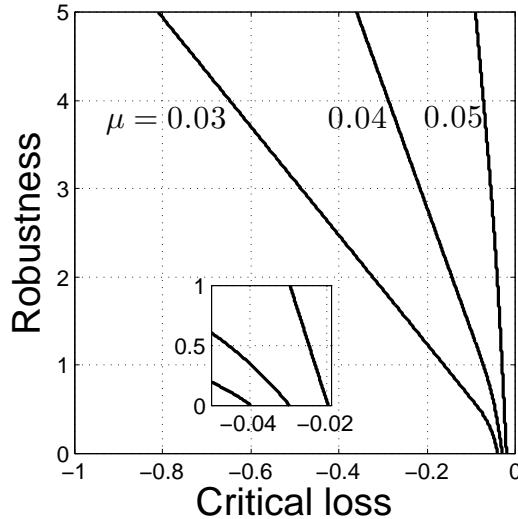


Figure 13: Robustness, \widehat{h} , vs. critical loss, R_C , for 3 values of μ . $\sigma = 0.03$.

§ Calibrating the robustness.

- Is robustness of 3 or 5 “large”?
- $\widehat{h} = 3$ means $3 \times$ tail is tolerable.
- Standard normal below -2σ : 0.0228 (small probab.)
-

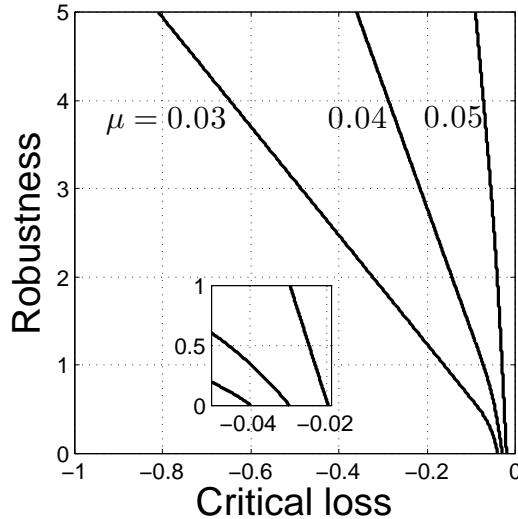


Figure 14: Robustness, \widehat{h} , vs. critical loss, R_C , for 3 values of μ . $\sigma = 0.03$.

§ Calibrating the robustness.

- Is robustness of 3 or 5 “large”?
- $\widehat{h} = 3$ means $3 \times$ tail is tolerable.
- Standard normal below -2σ : 0.0228 (small probab.)
- Fat tail below -2σ : 0.1080. (not small probab.)

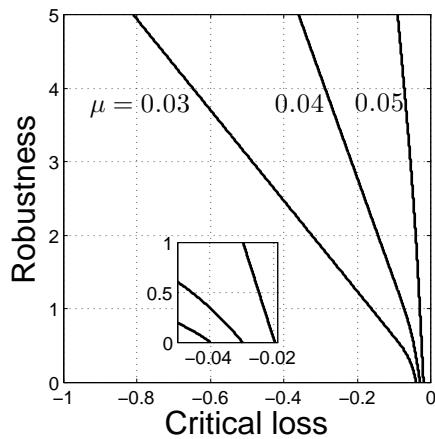


Figure 15: Robustness, \widehat{h} , vs. critical loss, R_C , for 3 values of μ . $\sigma = 0.03$.

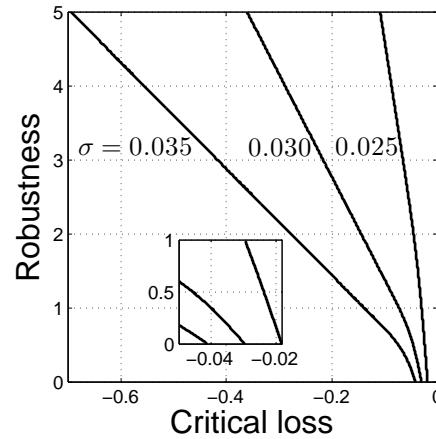


Figure 16: Robustness, \widehat{h} , vs. critical loss, R_C , for 3 values of σ . $\mu = 0.04$.

§ Mean-variance trade-off:

Increasing mean by 0.01
roughly equivalent to
decreasing st. dev by 0.005.

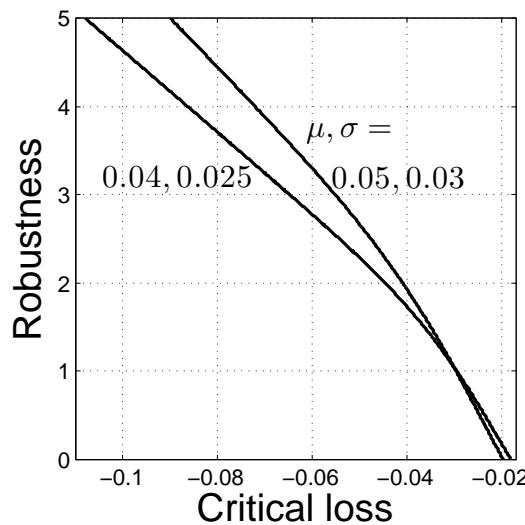


Figure 17: Robustness, \hat{h} , vs. critical loss, R_C , for two different combinations of μ and σ .

§ Preference reversal:

- $(\mu, \sigma) = (0.04, 0.025) \succ_{\text{est.}} (0.05, 0.03)$.
-

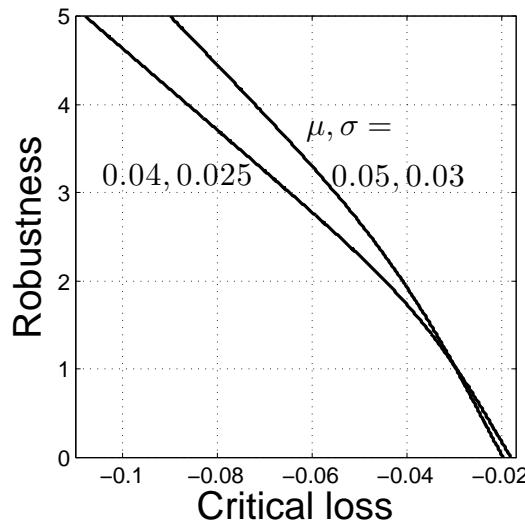


Figure 18: Robustness, \hat{h} , vs. critical loss, R_C , for two different combinations of μ and σ .

§ Preference reversal:

- $(\mu, \sigma) = (0.04, 0.025) \succ_{\text{est.}} (0.05, 0.03)$.
- $(\mu, \sigma) = (0.05, 0.03) \succ_{\text{rbs.}} (0.04, 0.025)$
at $\hat{h} > 1$.

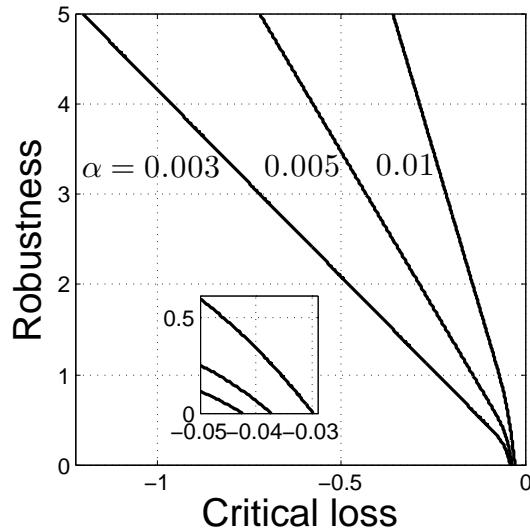


Figure 19: Robustness, \widehat{h} , vs. critical loss, R_C , for three different probabilities of failure, α . $\mu = 0.04$ and $\sigma = 0.03$.

§ Effect of greater probability of failure, α :

- **Greater robustness (curves shift right).**
-

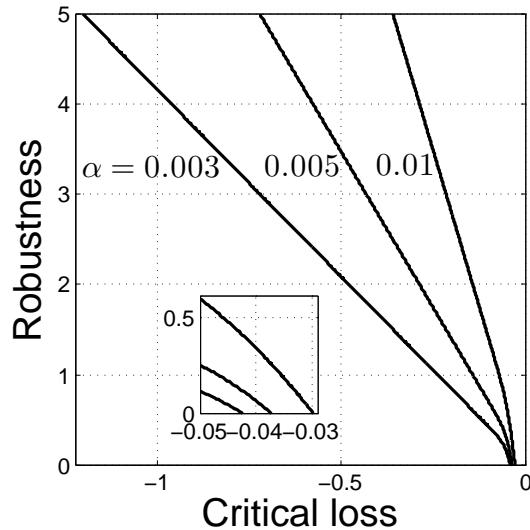


Figure 20: Robustness, \widehat{h} , vs. critical loss, R_C , for three different probabilities of failure, α . $\mu = 0.04$ and $\sigma = 0.03$.

§ Effect of greater probability of failure, α :

- **Greater robustness (curves shift right).**
- **Lower cost of robustness (steeper curves).**
-

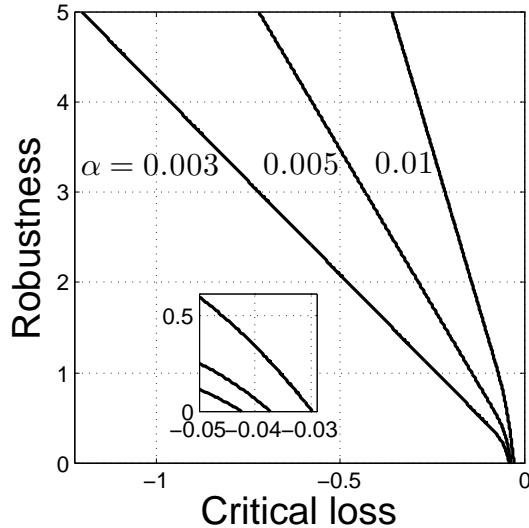


Figure 21: Robustness, \widehat{h} , vs. critical loss, R_C , for three different probabilities of failure, α . $\mu = 0.04$ and $\sigma = 0.03$.

§ Effect of greater probability of failure, α :

- **Greater robustness (curves shift right).**
- **Lower cost of robustness (steeper curves).**
- **Trade-offs: μ , σ and α .**

§ Less severe uncertainty:

- Thin tails.
- Known pdf family.
- Uncertain moments of normal pdf:

$$\mathcal{U}(h) = \left\{ p(r) \sim N(\mu, \sigma^2) : \left| \frac{\mu - \tilde{\mu}}{\varepsilon_\mu} \right| \leq h, \left| \frac{\sigma - \tilde{\sigma}}{\varepsilon_\sigma} \right| \leq h, \sigma \geq 0 \right\}$$

$$h \geq 0$$

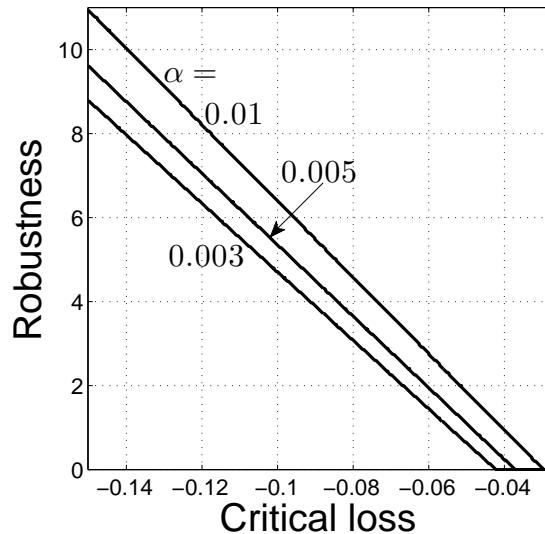


Figure 22: Robustness, \widehat{h} , vs. critical loss, R_C , for three different probabilities of failure, α .
 $\tilde{\mu} = 0.04$, $\tilde{\sigma} = 0.03$, $\varepsilon_\mu = 0.004$, $\varepsilon_\sigma = 0.003$.

§ Trade-off: Robustness vs. critical loss.

§ Zeroing: No robustness of estimated critical loss.

§

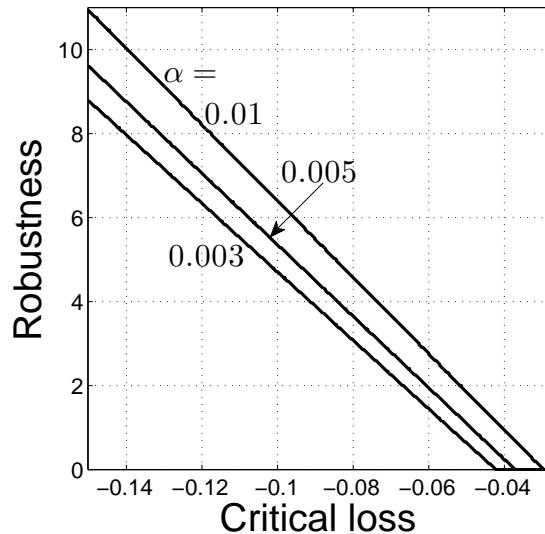


Figure 23: Robustness, \widehat{h} , vs. critical loss, R_C , for three different probabilities of failure, α .
 $\tilde{\mu} = 0.04$, $\tilde{\sigma} = 0.03$, $\varepsilon_\mu = 0.004$, $\varepsilon_\sigma = 0.003$.

§ **Trade-off:** Robustness vs. critical loss.

§ **Zeroing:** No robustness of estimated critical loss.

§ **Robustness:** Greater than for fat tails.

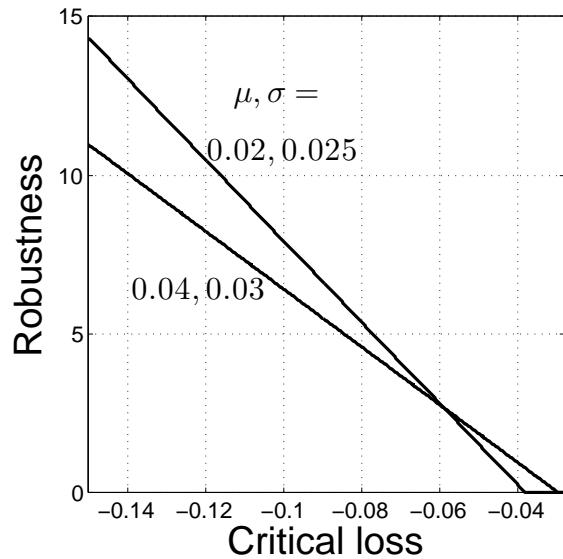


Figure 24: Robustness, \widehat{h} , vs. critical loss, R_C , for two different combinations of μ and σ . $\alpha = 0.01$.

§ Preference reversal:

- $(\mu, \sigma) = (0.04, 0.03) \succ_{\text{est.}} (0.02, 0.025)$.
- $(\mu, \sigma) = (0.02, 0.025) \succ_{\text{rbs.}} (0.04, 0.03)$ at $\widehat{h} > 2$.

§ Summary:

- Uncertain pdf: fat tails.
-

§ Summary:

- Uncertain pdf: fat tails.
- Nominal estimates: zero robustness.
-

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- Uncertain pdf: fat tails.
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 - Robustness vs performance.
 - Mean vs variance.
 - Mean vs failure probability.
-

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- Uncertain pdf: fat tails.
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- Trade-offs:
 - Robustness vs performance.
 - Mean vs variance.
 - Mean vs failure probability.
- Cost of robustness.
-

§ Summary:

- Uncertain pdf: fat tails.
- Nominal estimates: zero robustness.
- Trade-offs:
 - Robustness vs performance.
 - Mean vs variance.
 - Mean vs failure probability.
- Cost of robustness.
- Preference reversal between options.
-

§ Summary:

- Uncertain pdf: fat tails.
- Nominal estimates: zero robustness.
- Trade-offs:
 - Robustness vs performance.
 - Mean vs variance.
 - Mean vs failure probability.
- Cost of robustness.
- Preference reversal between options.
- Uncertainty judgment, info-gap model.

Any Questions?