Gordon-Loeb model and the mystery of 1/e

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Large and small, for-profit or not, modern organizations are struggling with managing their information technology (IT) assets, trying to make them secure at reasonable cost.

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Henceforth, our basic assumption is that given investment z, the expected loss is LS(z) for some function S.

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Risk neuronal condies that the optimal security investment should be the value z, and the total expected loss and the costs of mitigation, solving

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Risk neutrality implies that the optimal security investment should be the value *z*_{*} minimizing the total expected loss and the costs of mitigation, solving

$$\min_{z>0}(LS(z)+z).$$
 (1)

Thus we are facing a minimization problem:

 $\min_{z>0}(LS(z)+z).$ (2)

Following customary economic intuition Gordon and Loeb postulated that the function S is

- differentiable;
- non-increasing;
- > converges to 0 as $z \rightarrow \infty$, and
- is convex.

Further, Gordon and Loeb investigated two natural parametric families of functions S satisfying these requirements and found, remarkably, that

the optimal investment z_* does not exceed 1/e-th fraction of the total value at risk:

 $z_* \leq L/e$.

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And what about other functions?

It is easy to construct functions S, satisfying all of the properties above, yet such that the optimal investment levels z_* are *arbitrarily close* to the total value at risk L, see **Willemson'06**, **Hausken'06** (obviously, a risk neutral agent will not spend more on risk mitigation than the expected risk itself).

Here is the idea:



My contribution to the problem is twofold:

- I introduce an axiomatic framework allowing to recover G& L's setup from first principles, and
- I show that the resulting functions S do in fact imply the 1/e rule.

Let's start.

Where these functions S are coming from? Let's look at the roots.

I posit that the mitigation process consists of a variety of independent actions (like installs of software patches), each of which reducing the loss probability insignificantly and similarly requiring small investment.

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axioms

A0 We assume that elementary protective actions are elements of a separable measurable space (Ω, F), and that the protective actions are tantamount to measurable subsets of Ω.
To each (measurable) subset A ⊂ Ω, we can associate

- the cost z(A) of protective measure A, and
- the residual security risk s(A).

Informally, this axiom expresses the *smallness* of individual protective actions.

A1 We will assume the costs of protective actions are additive: in other words, figibint actions A_1, A_2 ,

 $z(A_1 \amalg A_2) = z(A_1) + z(A_2).$

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axioms, cont'd

A2 Similarly, we will require that the residual security risks are *multiplicatively* independent, i.e. for disjoint A_1, A_2 ,

 $s(A_1 \amalg A_2) = s(A_1)s(A_2).$

so that $u := \log(s)$ is a (non-positive), non-atomic measure on Ω .

A3 Lastly, we have that achieving perfect protection cannot be free, i.e. the second of the vector valued measure (s, u),

 $\{(z(A), u(A)), A \in \mathcal{F}\}$

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The range

$\{(z(A), u(A)), A \in \mathcal{F}\}$

of the measures z, u encodes the potential possibilities of investment into IT security for the firm.

We can now recover S(z) assuming that this is the best residual risk a protective action A feasible under the budget z can achieve.

from measures to functions, cont'd

Formally, let us define

$$S(z) = \inf_{A \in \mathcal{F}: z(A) \leq z} s(A) = \exp(\inf_{A \in \mathcal{F}: z(A) \leq z} u(A)).$$



Lyapunov convexity

Proposition

Under Axioms A0-A3,

a) the range of the (vector-valued) mapping

 $A\mapsto (z(A), u(A))$

is a convex closed subset $R \subset \mathbb{R}^2$ (in fact, a proper subset of the forth quadrant $\{z \ge 0, u \le 0\}$).

- b) for any z, the value S(z) is attained on a protective measure $A \in \mathcal{F}$;
- c) the function $v : z \mapsto \log(S(z))$ is convex.

Lyapunov convexity, cont'd

In other words, *S* is well defined, non-increasing, and *log-convex* (hence, convex).



1/e rule vindicated

Theorem

Let S be a non-increasing nonnegative log-convex function, and z_* is a solution to the optimization problem

 $\min_{z\geq 0} LS(z)+z.$

Then

 $z_* \leq L/e. \tag{3}$

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quick proof

Denote by f(z) := LS(z), and set z_* to be a point where f(z) + z attains its minimum on $[0, \infty)$. Then f lies above the linear function $l(z) := f(z_*) + (z_* - z)$ (and touches it at z_*), and, by log-convexity, also lies above some exponential function $a \exp(-qz)$ that is tangent to l at z_* .

 $aq \exp(-qz_*) = 1$, and $f(z) \geq a \exp(-qz),$ particular $f(0) \geq a$.

Now

$$\frac{z_*}{f(0)} \leq \frac{z_*}{a} = \frac{qz_*}{\exp(qz_*)} \leq 1/e.$$

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An obvious and interesting generalization is to move to general topologies: what are the optimal placements of filters there? are there any convexity properties? thus far, unknown...



The End