

More properties of the leakage

- $H(S) = H_\infty(S) = 0$ iff S is a point probability distribution (aka delta of Dirac), i.e., all the probability mass is in one single value
- The maximum value of $H(S)$ and $H_\infty(S)$ is $\log \#S$
- Shannon mutual information is symmetric: $I(S;O) = I(O;S)$
Namely: $H(S) - H(S|O) = H(O) - H(O|S)$.
This does not hold for the min-entropy case
- If the channel is deterministic, then $I(S;O) = H(O)$
- If the channel is deterministic, then $C_\infty = C = \log \#O$

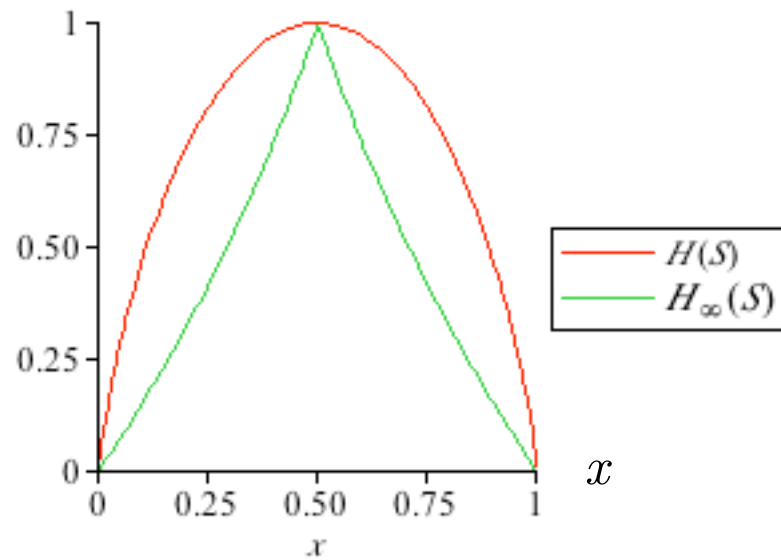
Exercises

1. Prove that $I_\infty(S;O) \geq 0$
2. Prove that if all rows of the channel matrix are equal, then $I_\infty(S;O) = 0$
3. Prove that all rows of the channel matrix are equal if and only if $C_\infty = 0$
4. Compute Shannon leakage and Rényi min-leakage for the password checker (the version where the adversary can observe the execution time), assuming a uniform distribution on the passwords

Rényi min-entropy vs. Shannon entropy

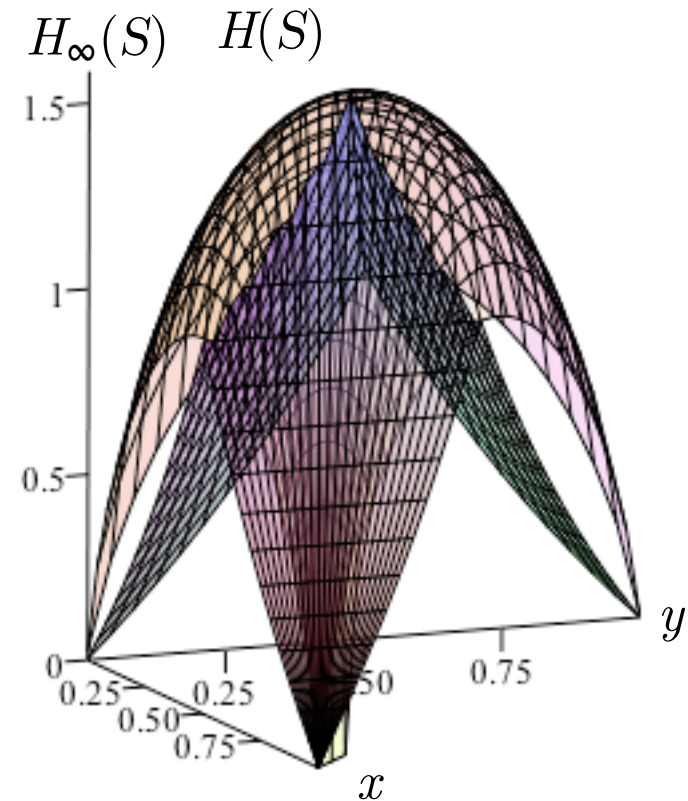
$$S = \{a, b\}$$

$$p(a) = x \quad p(b) = 1 - x$$



$$S = \{a, b, c\}$$

$$p(a) = x \quad p(b) = y \quad p(c) = 1 - (x + y)$$

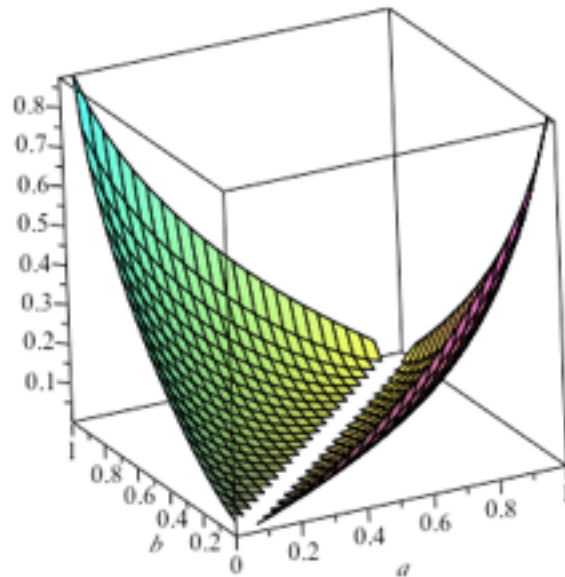


Rényi min entropy and conditional entropy are the log of piecewise linear functions

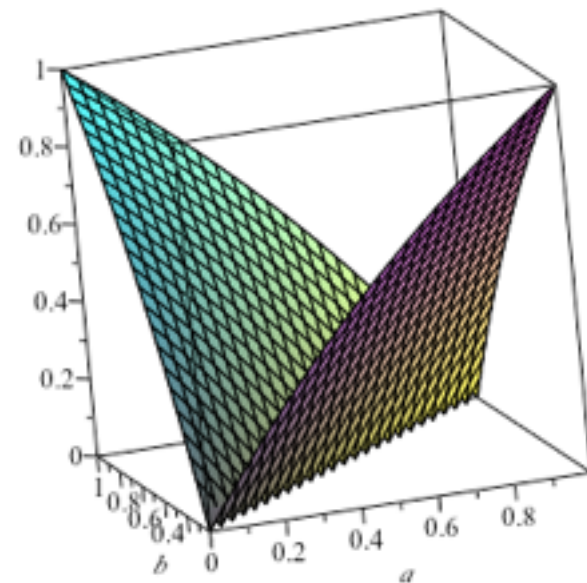
Shannon capacity vs. Rényi min-capacity

binary channel

a	$1-a$
b	$1-b$



Shannon capacity



Rényi min-capacity

In general, Rényi min capacity is an upper bound for Shannon capacity

Limitations of min-entropy leakage

- Min-entropy leakage implicitly assumes an operational scenario where adversary \mathcal{A} benefits only by guessing secret S **exactly**, and in **one try**.
- But many other scenarios are possible:
 - Maybe \mathcal{A} can benefit by guessing S **partially** or **approximately**.
 - Maybe \mathcal{A} is allowed to make **multiple** guesses.
 - Maybe \mathcal{A} is **penalized** for making a wrong guess.
- How can **any** single leakage measure be appropriate in all scenarios?

Notation

- π prior probability
- $x, x_1, x_2 \dots X$ secrets
- $x, y_1, y_2 \dots Y$ observables
- $w, w_1, w_2 \dots W$ guesses
(they may be different from the secrets)

Gain functions and g-leakage

- We generalize min-entropy leakage by introducing **gain functions** to model the operational scenario.
- In any scenario, there is a finite set \mathcal{W} of guesses that \mathcal{A} can make about the secret.
- For each guess w and secret value x , there is a **gain $g(w,x)$** that \mathcal{A} gets by choosing w when the secret's actual value is x .
- **Definition:** gain function $g : \mathcal{W} \times \mathcal{X} \rightarrow [0, 1]$
- **Example:** Min-entropy leakage implicitly uses

$$g_{\text{id}}(w,x) = \begin{cases} 1, & \text{if } w = x \\ 0, & \text{otherwise} \end{cases}$$

g-vulnerability and g-leakage

- Definition: **Prior g-vulnerability:**

$$V_g[\pi] = \max_w \sum_x \pi[x]g(w,x)$$

“ \mathcal{A} 's maximum expected gain, over all possible guesses.”

- **Posterior g-vulnerability:**

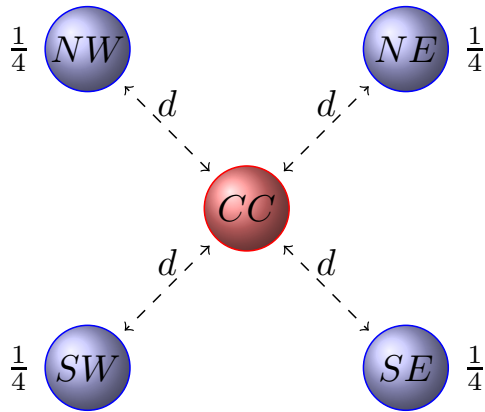
$$V_g[\pi, \mathbf{C}] = \sum_y p(y) V_g[p_{X|Y}]$$

- **g-leakage:** $\mathcal{L}_g(\pi, \mathbf{C}) = \log V_g[\pi, \mathbf{C}] - \log V_g[\pi]$
- **g-capacity:** $\mathcal{ML}_g(\mathbf{C}) = \sup_{\pi} \mathcal{L}_g(\pi, \mathbf{C})$

The power of gain functions

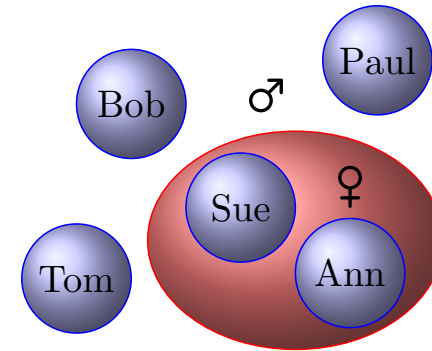
Guessing a secret **approximately**.

$$g(w,x) = 1 - \text{dist}(w,x)$$



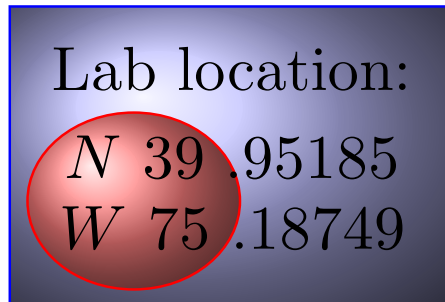
Guessing a **property** of a secret.

$$g(w,x) = \text{Is } x \text{ of gender } w?$$



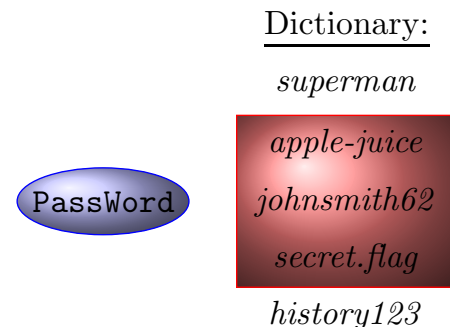
Guessing a **part** of a secret.

$$g(w, x) = \text{Does } w \text{ match the high-order bits of } x?$$



Guessing a secret in **3 tries**.

$$g_3(w, x) = \text{Is } x \text{ an element of set } w \text{ of size } 3?$$



Distinguishing channels with gain functions

- Two channels on a uniformly distributed, 64-bit x :
 - A. $y = (x \text{ or } 00000\dots 0111)$;
 - B. $\text{if } (x \% 8 == 0) \text{ then } y = x; \text{ else } y = 1$;
 - A always leaks all but the last three bits of x .
 - B leaks all of x one-eighth of the time, and almost nothing seven-eighths of the time.
 - Both have min-entropy leakage of 61 bits out of 64.
- We can distinguish them with gain functions.
- g_8 , which allows 8 tries, makes A worse than B.
- g_{tiger} , which gives a penalty for a wrong guess (allowing “ \perp ” to mean “don’t guess”) makes B worse.

Robustness worries

- Using g-leakage, we can express precisely a rich variety of operational scenarios.
- But we could worry about the **robustness** of our conclusions about leakage.
- The g-leakage $\mathcal{L}_g(\pi, C)$ depends on both π and g .
 - π models adversary \mathcal{A} 's **prior knowledge** about X
 - g models (among other things) what is **valuable** to \mathcal{A} .
- How confident can we be about these?
- Can we minimize sensitivity to questionable assumptions about π and g ?

Capacity results

- **Capacity** (the maximum leakage over all priors) eliminates assumptions about the prior π .
- Capacity relationships between **different** leakage measures are particularly useful.
- **Theorem:** Min-capacity is an upper bound on Shannon capacity: $\mathcal{ML}(\mathbf{C}) \geq SC(\mathbf{C})$.
- **Theorem (“Miracle”):** Min-capacity is an upper bound on g-capacity, for **every** g : $\mathcal{ML}(\mathbf{C}) \geq \mathcal{ML}_g(\mathbf{C})$.
 - Hence if \mathbf{C} has small min-capacity, then it has small g-leakage under **every** prior and **every** gain function.
 - (Note that the choice of g **does** affect both the prior and the posterior g-vulnerability.)