

Information-theoretic characterization of the Subregular Hierarchy

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Goal

To **link two notions of complexity**:

- **Formal language theory** (FLT) (Hopcroft and Ullman, 1979; Heinz, 2018)
- **Statistical complexity theory** (Feldman and Crutchfield, 1998)

Why?

Statistical complexity theory quantifies the **memory requirements** for generating a sequence incrementally. Limitations of human working memory may explain why natural language occupies the formal complexity class that it does.

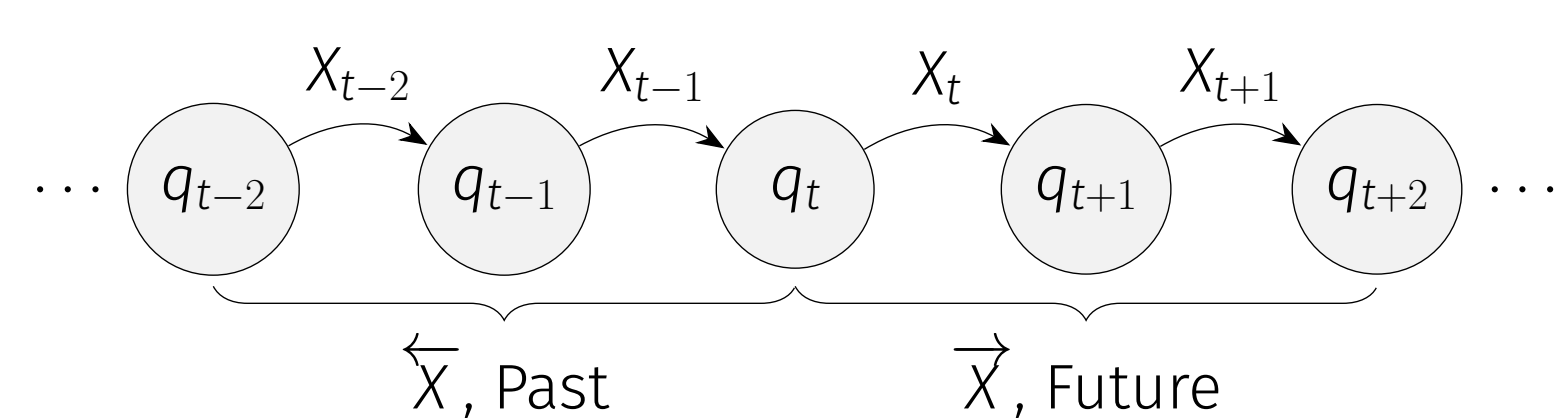
Probabilistic Deterministic Finite-State Automata (PDFAs)

A Probabilistic Deterministic Finite-State Automaton (PDFa) has:

- **Internal states** Q , an **alphabet** Σ ,
- an **emission distribution** $O : Q \rightarrow \Sigma$ (a stochastic function), and
- a **transition function** $T : Q \times \Sigma \rightarrow Q$ (a deterministic function).

To construct a stochastic process from a PDFa: whenever the PDFa emits an end-of-word symbol, let it transition back into its initial state. The resulting infinite stream of symbols is a **stationary ergodic stochastic process**.

- Let X be any stochastic process generating sequences of symbols indexed as $\dots X_{t-2}, X_{t-1}, X_t, X_{t+1}, \dots$



Statistical Complexity

The statistical complexity of X is the minimal amount of information about the past which must be stored in incremental memory in order to correctly generate the future:

$$S \equiv \min_{M: D_{KL}[\vec{X} | \vec{X} | \vec{X} | M] = 0} H[M],$$

$$\text{where } H[M] \equiv - \sum_x p_M(x) \log p_M(x).$$

Statistical complexity breaks into two terms (where $I[X : Y]$ is **mutual information**):

$$S = H[M] = I[M : \vec{X}] + H[M | \vec{X}] \\ = \underbrace{I[\vec{X} : \vec{X}]}_E + \underbrace{H[M | \vec{X}]}_C$$

Some Example PDFAs

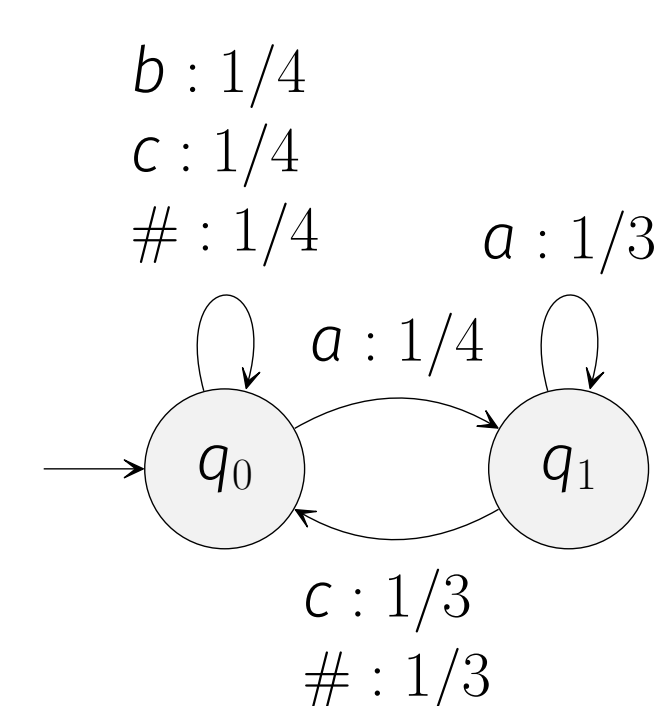


Figure 1: SL_2 PDFa of $-ab$, $\Sigma = \{a, b, c\}$

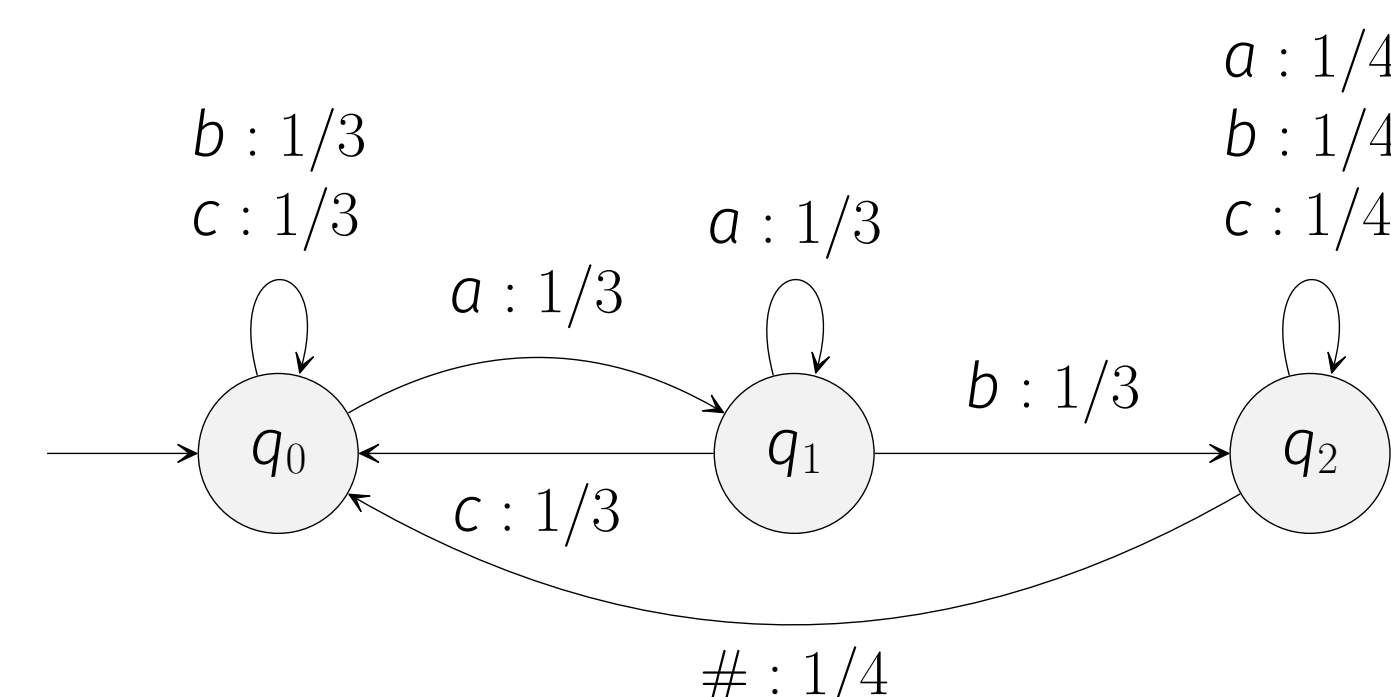


Figure 2: LT_2 PDFa of $\text{Some-}ab$, $\Sigma = \{a, b, c\}$

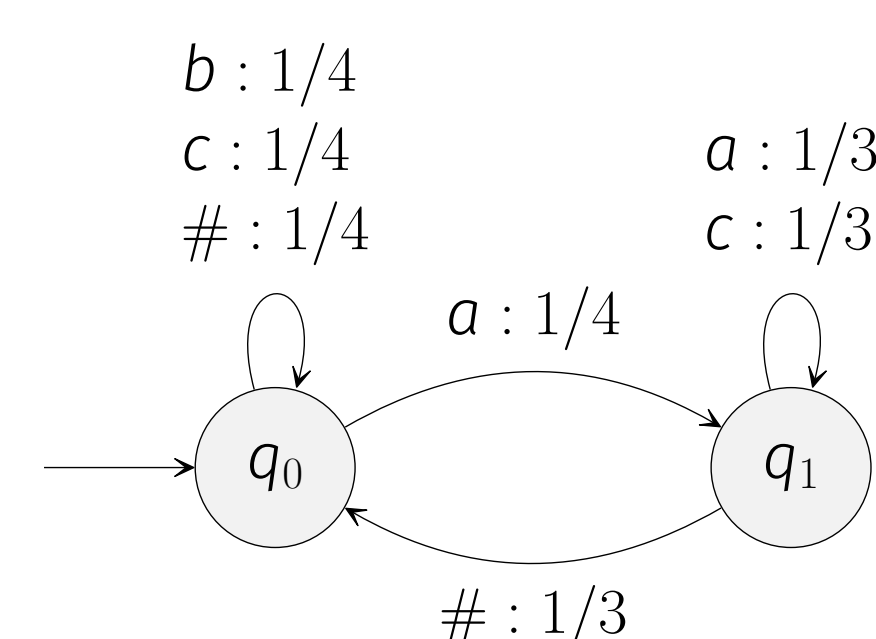


Figure 3: SP_2 PDFa of $-a \dots b$, $\Sigma = \{a, b, c\}$

Calculation of Quantities for PDFAs

- The **statistical complexity** in a minimal PDFa is the entropy of the stationary distribution Q over states, given by the first left eigenvector of the state transition matrix, whose entries are given by:

$$p(q_{t+1}|q_t) = \sum_{x_t \in \Sigma} p_O(x_t|q_t) \delta_{q_{t+1}=T(q_t, x_t)}.$$

- For SL_r languages, **excess entropy** $E = I[X_{t-r+1}, \dots, X_{t-1} : X_t, \dots, X_{t+r-1}]$.
- For other languages, an SL_r approximation always gives a **lower bound on E** (Travers and Crutchfield, 2011). We compute lower bounds on E from SL_7 approximations.

Quantities

- **Excess entropy E** is the amount of information in the past which is actually used to predict the future.
- **Crypticity C** is the amount of information which must be stored, but which ends up being useless.
- **E/S ratio** is the proportion of bits stored in memory which end up being useful.

Main Result

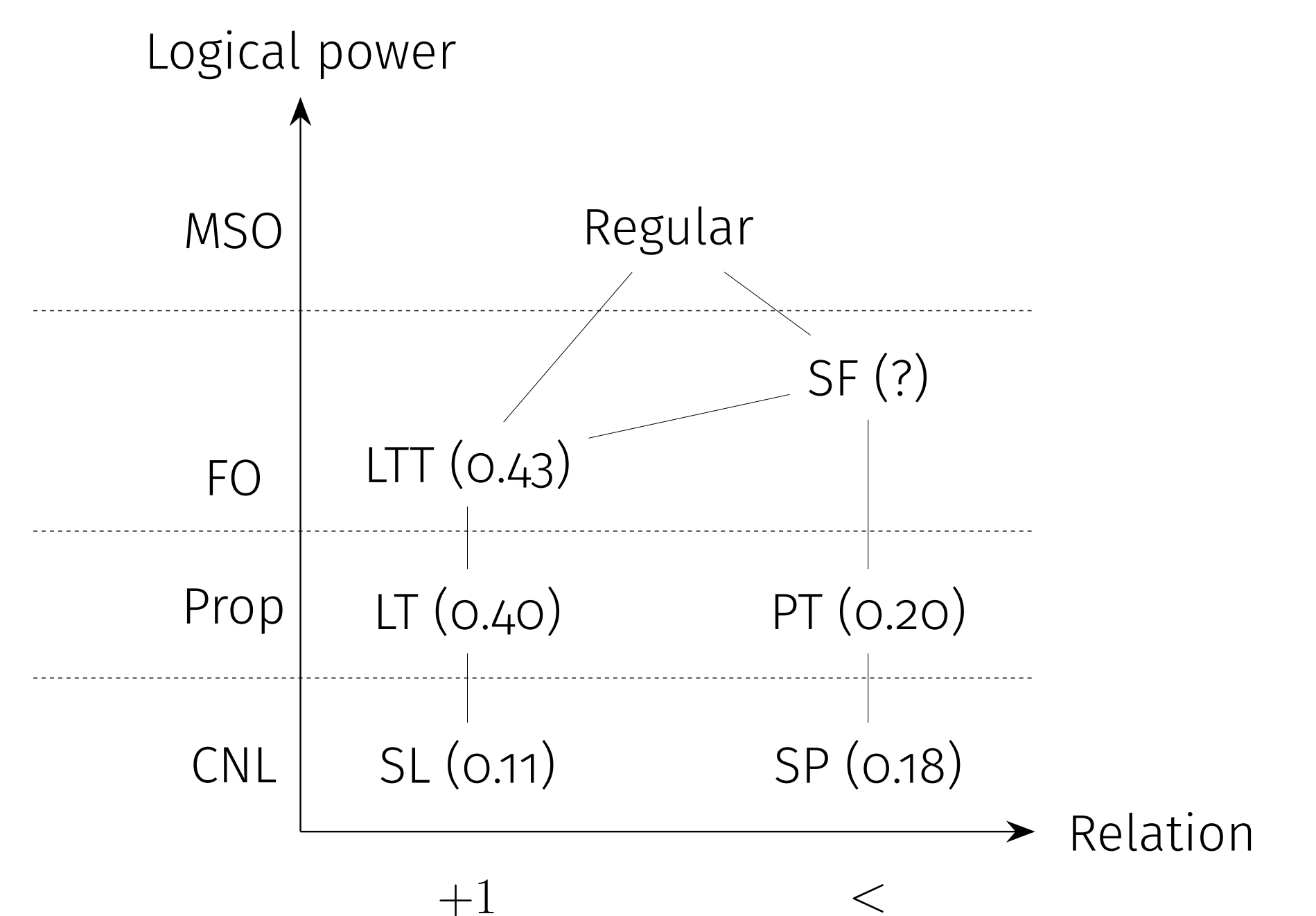
In a **series of example languages**, we find that increasing FLT complexity in the subregular hierarchy correlates with **E/S ratio**.

	SL_2	LT_2	LTT_2	SP_2	PT_2
S	0.97	1.53	1.94	0.99	1.53
E	0.09	≥ 0.61	≥ 0.83	≥ 0.18	≥ 0.30
C	0.75	≤ 0.91	≤ 1.10	≤ 0.80	≤ 1.22
E/S	0.11	≥ 0.40	≥ 0.43	≥ 0.18	≥ 0.20

Table 1: Information quantities for PDFAs

Conclusion

Based on our examples, we **conjecture** that crypticity correlates with logical power in the subregular hierarchy. In future work, we will formalize this idea.



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