1 Model Framework

We no longer focus on Markov chains, so the associated symbols like S and n no longer carry the same meaning. We will redefine them shortly. Also, in order for the polynomials to be well defined later, we will constrain $\tau > 0$.

We are interested in models with asymptotically power-law decay of the mutual information measure with respect to the distance between the tokens in the sequence. So far so good. But what does it *actually* mean?

The tokens, represented by random variables X_t , are elements of a finite alphabet Σ . The distance between X_t and $X_{t+\tau}$ is τ , and for every t and every τ we want to bound

$$I(X_t, X_{t+\tau}) \in \Omega(\tau^{-\alpha}), \ I(X_t, X_{t+\tau}) \in \mathcal{O}(\tau^{-\beta})$$

for some fixed $\alpha, \beta \in \mathbb{R}_{>0}$. The first condition is the important one, while the latter ensures that $I(X_t, X_{t+\tau}) \xrightarrow{\tau \to \infty} 0$. We also may replace the latter condition by this one.

This was straight forward. The challenging part is to define what a model is. In the case of Markov chains this seems trivial: We define a finite set of parameters (the transition probabilities), and we get a model over Σ^* , that is for every $n \in \mathbb{N}$ the model defines a probability measure over Σ^n . Thus:

Definition 1.1 (Model over Σ^*). A model S over Σ^* is a function $S: \mathbb{N} \times \Sigma^* \mapsto [0,1], \ (n,w) \mapsto p, \text{ for } n \in \mathbb{N}, \ w \in \Sigma^n, \ p \in [0,1] \text{ s.t. } \sum_{w \in \Sigma^n} S(n,w) = 1. \ S$ assigns the probability p to the word w of length n.

But really, we want to restrain S in order to have reasonable time and space complexity, and to ensure the model is reasonable, which means that the language of $S_n(w)$ should look similar to $S_{n+d}(w)$, whatever this might mean, where we used the notation $S_n(w) \equiv S(n, w)$. We also write w_i for X_i . Really, w is a 1-indexed String of X_i .

We present one strict definition for this *similarity* in the following definition:

Definition 1.2. We say S is well-behaved iff for every $n \in \mathbb{N}, w \in \Sigma^{n+1}$ it holds true that

$$\sum_{w_{n+1} \in \Sigma} S_{n+1}(w) = S_n(w_{-(n+1)}) .$$

Remark 1.1. Markov chains and hidden Markov models are well-behaved.

Lemma 1.1. For every $d \in \mathbb{N}$, let $I := [n+d] \setminus [n] = \{n+1, \ldots, n+d\}$. Then,

if S is well-behaved, we have for every $w \in \Sigma^{n+d}$:

$$\sum_{w_I \in \Sigma^d} S_{n+d}(w) = S_n(w_{-I}) \quad .$$

Proof. We use induction over d. The base case follows directly from the definition of S being well-behaved. Thus, assume the claim holds for some d := k. Then we have

$$\begin{split} \sum_{w_I \in \Sigma^{k+1}} S_{n+k+1}(w) &= \sum_{w_{I \backslash \{k+1\}} \in \Sigma^k} \sum_{w_{k+1} \in \Sigma} S_{n+k+1}(w) \\ &= \sum_{S \text{ well-defined } \sum_{w_{I \backslash \{k+1\}} \in \Sigma^k} S_{n+k}(w_{-\{k+1\}}) \\ &= \sum_{\text{induction hypothesis}} S_n(w_{-I}) \quad , \end{split}$$

which concludes the induction step.

Definition 1.3 (Induced Well-Behaved Model). Based on the model S, we can construct the *induced well-behaved* model S^* by defining S_n^* recursively as

•
$$S_1^* \coloneqq S_1$$
,

•
$$S_{n+1}^*(w) := S_n^*(w_{-\{n+1\}}) \frac{S_{n+1}(w)}{\sum_{w_{n+1} \in \Sigma} S_{n+1}(w)}$$
.

Remark 1.2. If
$$\frac{S_{n+1}(w)}{\sum_{w_{n+1} \in \Sigma} S_{n+1}(w)} = \frac{0}{0}$$
, we might set $\frac{S_{n+1}(w)}{\sum_{w_{n+1} \in \Sigma} S_{n+1}(w)} \coloneqq \frac{1}{|\Sigma|}$.

Lemma 1.2. The induced well-behaved model S^* is indeed well-behaved. Proof. We have:

$$\sum_{w_{n+1} \in \Sigma} S_{n+1}^*(w) = \sum_{w_{n+1} \in \Sigma} S_n^*(w_{-\{n+1\}}) \frac{S_{n+1}(w)}{\sum_{w_{n+1} \in \Sigma} S_{n+1}(w)}$$

$$= \frac{S_n^*(w_{-\{n+1\}})}{\sum_{w_{n+1} \in \Sigma} S_{n+1}(w)} \sum_{w_{n+1} \in \Sigma} S_{n+1}(w)$$

$$\stackrel{\checkmark}{=} S_n^*(w_{-\{n+1\}}) .$$

Now, we want to look at how we might restrict our model $(S_n)_{n\in\mathbb{N}} \equiv S$. One approach might be to define a model structure for every $n \in \mathbb{N}$. To this end, we

define S_n by some finite parameters θ_n over the model space $S(n) \equiv S_n$, which specifies the structure of our models. Thus:

$$S_n \in \{S_n(\boldsymbol{\theta}_n) : \boldsymbol{\theta}_n \in \Theta_n\} =: \mathcal{S}_n$$

where Θ_n is the set of all possible parameters of S_n . We write S_{n,θ_n} for S_n with parameters θ_n . Hence, $(S_n)_{n\in\mathbb{N}}$ is completely defined by $(S_n,\theta_n)_{n\in\mathbb{N}}$.

Remark 1.3. The parameter space Θ_n may consist of parameter vectors with varying lengths. The same model S_n may be defined by two parameter vectors with very different sizes over the same model space S_n or potentially two different model spaces. Thus, the parametrization complexity depends of the model space S.

Definition 1.4 (Family of Models). We say $(S_n)_{n\in\mathbb{N}}$ is a *family of models* over the model space S iff $S_n \in S_n$ for every $n \in \mathbb{N}$. As a shorthand, we write $S \in S$.

For our model S, we want power-law decay in the mutual information with respect to τ between any two variables X_t , $X_{t+\tau}$, i.e. it has to hold for every t and every S_n . But what does this actually mean?

Definition 1.5. We define $i_{S_n}(\tau)$ and $I_{S_n}(\tau)$ to be the minimal and maximal mutual information between any two variables of S_n with distance τ . Formally, let $X_t, X_{t+\tau}$ $(t+\tau \leq n)$ be random variables with distributions defined by S_n . Then:

- $i_{S_n}(\tau) := \min_{t \in [n-\tau]} I(X_t, X_{t+\tau})$,
- $I_{S_n}(\tau) := \max_{t \in [n-\tau]} I(X_t, X_{t+\tau})$.

Definition 1.6 (Strong Power-Law Behavior). A model S has $strong\ lower-bound\ power-law\ behavior$ iff there exist constants $c, \alpha \in \mathbb{R}_{>0}$ s.t. for every $n \in \mathbb{N}$ it holds true that $i_{S_n}(\tau) \geq c\tau^{-\alpha}$. Similarly, S has $strong\ upper\ bound\ power-law\ behavior$ iff there exist constants $c', \alpha' \in \mathbb{R}_{>0}$ s.t. for every $n \in \mathbb{N}$ it holds true that $I_{S_n}(\tau) \leq c'\tau^{-\alpha'}$. Furthermore, S has $decaying\ behavior$ iff for every $n \in \mathbb{N}$ we have $I_{S_{n+\tau}}(\tau) \xrightarrow{\tau \to \infty} 0$. Lastly, S has $strong\ power-law\ behavior$ iff it has strong lower and upper bound power-law behavior (alternatively decaying behavior instead of strong upper bound power-law behavior).

Corollary 1.1 (Strong Power-Law Behavior for Well-Behaved Models). For a well-behaved model S^* we can replace "for every $n \in \mathbb{N}$ " in definition 1.6 with "for $n \to \infty$ " thanks to lemma 1.1.

Definition 1.7. We define $\overline{i_{S_n}}$ and $\overline{I_{S_n}}$ to be the minimal and maximal mutual information between any two variables of S_n with arbitrary distance τ . Formally, let X_i, X_j $(1 \le i < j \le n)$ be random variables with distributions defined by S_n . Then:

- $\overline{i_{S_n}} := \min_{(i,j) \in [n]^2, i < j} I(X_i, X_j) = \min_{\tau \in [n-1]} i_{S_n}(\tau)$,
- $\overline{I_{S_n}} := \max_{(i,j) \in [n]^2, i < j} I(X_i, X_j) = \max_{\tau \in [n-1]} I_{S_n}(\tau)$.

Definition 1.8 (Weak Power-Law Behavior). A model S has weak lower bound power-law behavior iff $\overline{i_{S_n}} \in \Omega(n^{-\alpha})$ for some $\alpha \in \mathbb{R}_{>0}$. Similarly, S has weak upper bound power-law behavior iff $\overline{I_{S_n}} \in \mathcal{O}(n^{-\beta})$ for some $\beta \in \mathbb{R}_{>0}$. Lastly, S has weak power-law behavior iff it has weak lower and upper bound power-law behavior (alternatively decaying behavior instead of weak upper bound power-law behavior).

Remark 1.4. Weak power-law behavior does *not* imply strong power-law behavior, not even for well-behaved models. To see this, note that we might have $i_{S_n}(1) \xrightarrow{n \to \infty} 0$ for some models with weak lower bound power-law behavior. $(S_n \text{ may force } i_{S_n}(1) \text{ to decay to } 0 \text{ for } n \to \infty \text{ because of weak correlations of consecutive tokens very late in the sequence.)$

Proposition 1.1 (Every Token has Power-Law Decay in well-behaved Models with Weak Power-Law Behavior). Let S be a well-behaved model with weak power-law behavior. Then, there exists an α , $\beta \in \mathbb{R}_{>0}$ s.t. for every X_t , $I(X_t, X_{t+\tau}) \in \Omega(\tau^{-\alpha})$ and $I(X_t, X_{t+\tau}) \in \mathcal{O}(\tau^{-\beta})$ (where X_t and $X_{t+\tau}$ are sampled over $S_{t+\tau}$, or, equivalently, any $S_{t+\tau+k}$).

Proof. We may only prove the existence of α , as the claim for β follows similarly. Since S has weak power-law behavior, there exist α' , $c' \in \mathbb{R}_{>0}$ s.t. $\overline{i_{S_n}} \geq c' n^{-\alpha'}$. Then, for every $t \in \mathbb{N}$, we have for $n \coloneqq t + \tau$ by the definition of $\overline{i_{S_n}}$:

$$I(X_t, X_{t+\tau}) \ge \overline{i_{S_{t+\tau}}}$$

$$\ge c'(t+\tau)^{-\alpha'}$$

$$= c'\tau^{-\alpha'}(\frac{t}{\tau}+1)^{-\alpha'}$$

$$\ge c'\tau^{-\alpha'}(t+1)^{-\alpha'}$$

Since S is well-behaved, this inequality holds when sampling over any $S_{t+\tau+k}$, $k \in \mathbb{N}$. Now, set $\alpha := \alpha'$ and $c := c'(t+1)^{-\alpha'}$. Note that α does not depend on t. Finally, we see that $I(X_t, X_{t+\tau}) \geq c\tau^{-\alpha}$. Thus, we get $I(X_t, X_{t+\tau}) \in \Omega(\tau^{-\alpha})$. \square

Theorem 1.1. Strong lower bound power-law behavior implies weak lower bound power-law behavior, and, similarly, strong upper bound power-law behavior implies weak upper bound power-law behavior.

Proof. TODO.
$$\Box$$

Proposition 1.2 (Upper Bound Power-Law Behavior implies Decaying Behavior). Weak upper bound power-law behavior implies decaying behavior (and hence so does strong upper bound power-law behavior).

Proof. TODO. \Box