## <span id="page-0-0"></span>Adaptive compression over countable alphabets

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## <span id="page-1-0"></span>Lossless compression over a countable alphabet

#### Lossless compression

Mapping messages (sequences of symbols from countable alphabet  $\chi$ ) to codewords (sequences of {0, <sup>1</sup>}), so as to minimize the expected length of codewords in a one-to-one and non-ambiguous way.

Non-ambiguous codes satisfy Kraft-McMillan inequality

For 
$$
\lambda: A \to \mathbb{N}_+
$$
,

 $\sum_{\omega \in A} 2^{-\lambda(\omega)} \leq 1$ , iff ∃ non-ambiguous code  $f : A \to \{0, 1\}^*$  with  $\ell[f(\omega)] = \lambda(\omega)$ ω∈*<sup>A</sup>*

#### Kraft-Mac Millan inequality

#### provides a bridge between codes and probability distributions

- . Any non-ambiguous code defines a (sub)-probability distribution over the set of messages
- . Any probability distribution *<sup>Q</sup>* over the set of messages defines a non-ambiguous encoding where codeword length is at most <sup>−</sup> log<sup>2</sup> *<sup>Q</sup>*([ω](#page-13-0)) + 1.

#### [Redundancy](#page-2-0) **[Redundancy, minimax](#page-2-0)**

## <span id="page-2-0"></span>Redundancy

Definition (Redundancy of coding probability *Q<sup>n</sup>* with respect to source *P n* )

Expected difference between codelengths obtained by feeding an arithmetic coder with *Q<sup>n</sup>* (**x**) rather than with the correct source statistics *P n* (**x**)

$$
D(P^n, Q^n) = \mathbb{E}_{P^n} \log \frac{P^n(X_{1:n})}{Q^n(X_{1:n})}
$$

Λ *n* is collection of probability distributions over messages of length *n*. Each probability distribution is called a source.

Definition (Minimax redundancy) Definition (Maximin redundancy)  $\pi$ : prior distribution on sources  $R^+(\Lambda^n)$  = inf sup *P*∈∈Λ *D*(*P n* , *Qn* )  $R_+(\Lambda^n)$  = sup inf  $\mathbb{E}_{\pi}D(P^n, Q^n)$ π **MinMax Theorem**  $) = R^{+}(\Lambda^{n})$ K ロ ▶ K 何 ▶ K 로 ▶ K 로 ▶ 그리고 K) Q (연 Information Theory, ... and Big Data 2015, S. Boucheron (Paris-[Adaptive compression](#page-0-0) March, 17th, 2015 3 / 19

## <span id="page-3-0"></span>Redundancies: alphabet size matters

Λ : memoryless sources over finite alphabet with cardinality *k*

Minimax redundancy

$$
R^+(\Lambda^n) = \frac{k-1}{2} \log \frac{n}{2\pi e} + O(1)
$$

Rissanen, Ryabko, Shtarkov, Krichevsky, Trofimov, Barron, Clarke, Xie et al..

Krichevsky-Trofimov coding is asymptotically maximin and approximately minimax

$$
\mathbb{K} \mathbb{T} \left( X_{n+1} = \mathbf{a} | X_{1:n} = X_{1:n} \right)
$$
  
= 
$$
\frac{n_{\mathbf{a}}(X_{1:n}) + \frac{1}{2}}{n + \frac{k}{2}},
$$

Countable alphabets

Negative results

$$
\exists (\mathbf{\Theta}^n)_n, \quad \forall P \in \Lambda, \n\lim_{n} \frac{1}{n} D(P^n, \mathbf{\Theta}^n) = 0
$$

iff

$$
\exists P^*, \quad \forall P \in \Lambda, \\
\mathbb{E}_{P^1} \left[ -\log P^*(X) \right] < \infty
$$

J. Kieffer (1993), Gyorfi, Pali van der Meulen (1993)

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 $E|E|$  or  $\alpha$ 

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## <span id="page-4-1"></span><span id="page-4-0"></span>Envelop classes

For stationary ergodic sources over a countable alphabet, no analogue of Lempel-Ziv coding.

To obtain positive results... it is necessary to impose constraints on source classes

#### Envelop function

$$
f\colon\mathbb{N}\to\mathbb{R}_+ \text{ with } 1<\sum_{j>0}f(j)<\infty.
$$

#### Envelop class

$$
\Lambda_f = \Big\{\mathbb{P} \ : \ \forall x \in \mathbb{N}, \ \mathbb{P}^1\{x\} \leq f(x) \text{ and } \mathbb{P} \text{ is stationary and memoryless.} \Big\}
$$

#### Envelope distribution

- 
$$
F(k) = 1 - \sum_{j>k} f(j)
$$
 for  $k \ge l_f := max\{k : \sum_{j\ge k} f(j) \ge 1\}$  envelope distribution  
-  $\overline{F} = 1 - F$  tail envelope function  
-  $U(t) = inf\{x : F(x) \ge 1 - 1/t\}$  tail quantile (envelope) function

## <span id="page-5-0"></span>Envelopes

#### Sub-exponential classes

- *F<sup>c</sup>* has non-decreasing hazard rate (ako log-concavity assumption)
- *U<sup>c</sup>* exp is concave.

#### Example

. ...

- **Exponential envelopes.**  $f(k) = \gamma e^{-\left(\frac{k}{\beta}\right)^2}$  $\int_{a}^{\alpha}$ , with  $\alpha \geq 1$ ,  $\beta > 0$ and  $\nu > 1$
- **Poisson envelopes**  $f(k) = \gamma e^{-\beta} \beta^k / k!$  with  $\beta > 0$  and  $\nu > 1$

#### Regularly varying envelops

*F<sup>c</sup>* (resp. *Uc*) is regularly varying with index  $-1/\gamma$  (resp.  $\gamma > 0$ )

$$
\forall x > 0, \qquad \lim_{t} \frac{F_c(tx)}{F_c(t)} = x^{-1/\gamma}
$$

$$
U_c(t)=t^{\gamma}\ell(t)
$$

where  $\ell$  is slowly varying

#### Example

- **Power-law envelopes:**  $U_c(t) = \kappa t^{\gamma}$
- **E.** Heavy-Tailed envelopes  $U_c(t) = \kappa t^{\gamma} \ell(t)$

## <span id="page-6-0"></span>Bounds on minimax redundancy

#### <span id="page-6-1"></span>Theorem [BGG, 2009]

If Λ is a class of memoryless sources, with the tail envelope distribution function  $\bar{F}_{\Lambda^1}(u) = \sum_{k>u} \hat{\rho}(k)$ , then:

$$
R^+(\Lambda^n) \leq \inf_{u:u\leq n} \left[ n\bar{F}_{\Lambda^1}(u) \log_2 e + \frac{u-1}{2} \log_2 n \right] + 2.
$$

#### Suggestion

If the envelop is known, choose threshold  $\tau$  as the solution of  $\bar{F}_{\Lambda}$ <sub>1</sub> $(u) = \frac{u}{n}$ .

- i) Encode symbols over threshold using Elias penultimate code
- ii) Encode other symbols using Krichevsky-Trofimov mixture over alphabet  $\{1,\ldots,\tau\}.$

If the envelop is not known, look for a data-driven threshold

# <span id="page-7-0"></span>Flavors of adaptivity

- For collections of small classes
- Definition [Asymptotic adaptivity]
- (*Q<sup>n</sup>* )*<sup>n</sup>* is asymptotically adaptive with respect to (Λ*m*)*m*∈M if

$$
\forall m \in \mathcal{M}, \quad R^+(\mathcal{Q}^n, \Lambda_m^n) = \sup_{\mathbb{P} \in \Lambda_m} D(\mathbb{P}^n, \mathcal{Q}^n) \leq (1 + o(1))R^+(\Lambda_m^n)
$$

For collections of massive envelop classes

Definition [Weak asymptotic adaptivity]

(*Q<sup>n</sup>* )*<sup>n</sup>* is asymptotically weakly adaptive with respect to (Λ*m*)*m*∈M

 $\forall m \in \mathcal{M}, \quad R^+(\mathcal{Q}^n, \Lambda_m^n) \leq o(\log n)R^+(\Lambda_m^n).$ 

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## <span id="page-8-0"></span>Censuring codes: sketch

#### <span id="page-8-1"></span>AC-code : Thresholding above last record

 $m_i = \max_{1 \le i \le i} x_i$ . The *j*<sup>th</sup> record is denoted by  $\widetilde{m}_j$  ( $\widetilde{m}_0 = 0$ ) Let  $\widetilde{\mathbf{m}} = (\widetilde{m}_i - \widetilde{m}_{i-1} + 1)$ . Symbols from  $\widetilde{m}$  encoded using Elias penultimate code.

Progressive KT coding below the last record

 $\widetilde{X}_i = X_i \mathbb{I}_{X_i \le m_{i-1}}.$ *C<sub>M</sub>* : progressive KT- encoding of  $\widetilde{X}_{1:n}$ <sup>O</sup>

$$
Q_{i+1}(\widetilde{X}_{i+1} = j | X_{1:i} = x_{1:i}) = \frac{n'_i + \frac{1}{2}}{i + \frac{m_i + 1}{2}} \quad \text{if} \quad 1 \leq j \leq m_i,
$$
  

$$
Q_{i+1}(\widetilde{X}_{i+1} = 0 | X_{1:i} = x_{1:i}) = \frac{1/2}{i + \frac{m_i + 1}{2}},
$$

where  $n_{j}^{j}$  is the number of occurrences of symbol  $j$  in  $x_{1:j}$  ,  $n_{j}^{0}=0$ . *i*

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## <span id="page-9-0"></span>Light-tailed envelopes

<span id="page-9-1"></span>The AC-code is adaptive with respect to source classes defined by envelopes with finite and non-decreasing hazard rate.

#### Theorem [B., Bontemps, Gassiat, 2014]

*Q<sup>n</sup>* : the coding probability associated with the AC-code, If *f* is an envelope with non-decreasing hazard rate,

 $R^+(\mathsf{Q}^n; \Lambda_f^n) \leq (1+o(1))R^+(\Lambda_f^n)$ 

while

$$
R^{+}(\Lambda_f^n) = (1 + o(1))(\log e) \int_1^n \frac{U_c(x)}{2x} dx
$$



## <span id="page-10-0"></span>Envelopes with heavier tails

If the tail envelope distribution is heavier than exponential, thresholding at maximum does not lead to (weakly) adaptive coding

Ideal threshold: solution of

 $t\overline{F}_c(u)=\frac{u}{2}\log t$ 

Proxy threshold: *m<sup>c</sup>* solution of

$$
t\overline{F}_c(u) = u \text{ or } u = U_c\left(\frac{t}{u}\right)
$$

#### **Properties**

- $\triangleright$   $m_c$  is non-decreasing.
- $\triangleright$  *m<sub>c</sub>*(*t*) ∕ ∞
- $\triangleright$   $m_c(t)/t \searrow 0$
- . If *<sup>U</sup><sup>c</sup>* is <sup>γ</sup>-regularly varying, *<sup>m</sup><sup>c</sup>* is  $\gamma/(\gamma + 1)$ -regularly varying.

#### Empirical theshold

 $M_n = \min (n, \{k : X_{k,n} \leq k\})$ 

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## <span id="page-11-0"></span>Weak adaptivity of ETAC encoding

<span id="page-11-1"></span>If 
$$
\overline{F}_c \in MDA(-1/\gamma)
$$
 with  $\gamma > 0$ ,

 $\forall \epsilon > 0$ , for sufficiently large *n*,  $\mathbb{E}X_{M_n,n} \leq m_n(1+\epsilon)$   $R^+(\Lambda_f^n) \geq \frac{m_n}{2}$ .

If *Q<sup>n</sup>* is the coding probability associated with the ETAC code  $R^+(\mathsf{Q}^n, \Lambda_n) \leq (5 + o_\Lambda(1)) \frac{m_n}{2}$  $\frac{n_n}{2}$  log  $n + 2$ 

B., Gassiat, Ohannessian, 2014

**For power law envelopes**  $U_c(t) = \kappa t^{\gamma}$  (Acharya et al. 2014)

$$
R^{+}(\Lambda_f^n) \sim \left(\frac{\kappa^{1/\gamma}}{\gamma}n\right)^{\frac{\gamma}{\gamma+1}}\left(\frac{1}{\gamma} + \gamma \log e + c\right)
$$

[Details](#page-19-1)

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### Thanks

I<mark>nformation Theory, ... and Big Data 2015, S. Bouch</mark>eron (Paris-[Adaptive compression](#page-0-0) March, 17th, 2015 13 / 19

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## <span id="page-14-1"></span><span id="page-14-0"></span>Envelop classes

#### Smoothed distribution function

- *F<sup>c</sup>* has piecewise constant hazard rate,
- $-F_c(n) = \overline{F}(n)$
- $-L_c(t) = \inf\{x: 1/\overline{F}_c(x) \ge t\}.$

If *X* ∼ *F<sub>c</sub>* then  $[X]$  + 1 ∼ *F* and  $U(t) = [U_c(t)]$  + 1 for *t* > 1.

#### Lemma [Stochastic comparison by quantile coupling]

There exists a probability space where  $X \sim G \in \Lambda_f$  ,  $Y \sim F_c$  such that

 $P{X \le Y} = 1$ 

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## <span id="page-15-0"></span>Bounds on minimax redundancy

Redundancy-Capacity theorem For any prior  $\mu$  on  $\Lambda^1(f)$ 

 $R^+(\Lambda^n) = I(\theta; X_{1:n})$ 

### For an ad hoc prior

 $I(\theta; X_{1:n}) \geq \mathbb{E}Z_n$ 

where *Z<sup>n</sup>* is the number of distinct symbols in *X*<sup>1</sup>:*<sup>n</sup>*

 $\mathbb{E} Z_n \geq m_n$ 

where  $m_n$  satisfies  $\overline{F}_c(m_n) \approx \frac{m_n}{n}$ 

Made in California

For light-tailed envelopes

$$
R^+(\Lambda_f^n) \sim \log(e) \int_1^n \frac{U_c(x)}{2x} \mathrm{d}x \left(1+o(1)\right)
$$

Bontemps, B. & Gassiat, 2014 using Haussler & Opper, AoS, 1997

For power law envelopes  $U_c(t) = \kappa t^{\gamma}$ 

$$
R^+(\Lambda_f^n) \sim \left(\frac{\kappa^{1/\gamma}}{\gamma}n\right)^{\frac{\gamma}{\gamma+1}} \left(\frac{1}{\gamma} + \gamma \log e + C\right)
$$

Acharya, J., Jafarpour, A., Orlitsky, A., & Suresh, A. T. (2014)

## Censuring codes: sketch

<span id="page-16-0"></span>

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## Light-tailed envelopes

<span id="page-17-0"></span>Decomposing redundancy of AC-code

Decomposing pointwise redundancy

$$
-\log Q^n(X_{1:n}) + \log \mathbb{P}^n(X_{1:n}) = \underbrace{\ell(C_{\mathsf{E}})}_{\mathsf{I}} + \underbrace{\ell(C_{\mathsf{M}}) + \log \mathbb{P}^n(X_{1:n})}_{\mathsf{II}}.
$$

Establishing main theorem in [BBG, 2014]

 $\rightarrow$ 

- $\triangleright$  (i) (Elias encoding of increments between records) is negligible with respect to  $R^+(\Lambda_f^n)$ , uniformly for  $\mathbb{P} \in \Lambda_f$ ,
- $\triangleright$  The expected value of (ii) is upper bounded, uniformly for  $\mathbb{P} \in \Lambda_f$ , by a term which is equivalent to  $P^+(N)$ which is equivalent to  $R^+(\Lambda_f^n)$ .

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## Light-tailed envelopes

#### Stochastic behavior of *M<sup>n</sup>*

Let  $X_1, \ldots, X_n \sim_{i.i.d.} P \in \Lambda_f^1$ , let  $M_n = \max(X_1, \ldots, X_n)$ , then,  $EM_n \leq U_c(en) + 1$  $\mathbb{E}[M_n \log M_n] \leq [U_c(en) + 1] \log [U_c(en) + 1] + 2/b^2$ 

#### Ingredients of proof

- . Rényi's representation of order statistics & concavity of *<sup>U</sup>* exp
- $\triangleright$  Sub-additivity of relative entropy (see Ledoux, 2001, Massart, 2006)<br> $\triangleright$  The entropy method  $\rightarrow$  sharp tail and moment bounds for order sta
- The entropy method  $\rightarrow$  sharp tail and moment bounds for order statistics (B. & Thomas, 2012)



## <span id="page-19-0"></span>Weak adaptivity of ETAC encoding

<span id="page-19-1"></span>

 $M_n = \min (n, \{k : X_{k,n} \leq k\})$ 

## $F_c \in MDA(\gamma), \gamma > 0$ *Mn mn*  $\stackrel{P}{\longrightarrow}$  1.  $\frac{X_{M_n,n}}{m_c(n)}$ *P* → 1.

#### *M<sup>n</sup>* is self-bounded

$$
\mathbb{P}\{|M_n - \mathbb{E}M_n| \geq t\}
$$
  
\$\leq 2e^{-\frac{t^2}{2(\mathbb{E}M\_{n}+t)}}\$.