CROQuant: Complex Rank-One Quantization Algorithm

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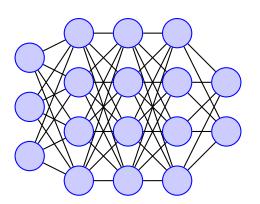
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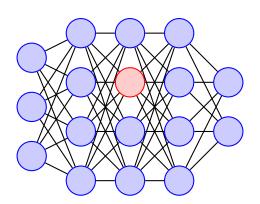




Main goal: Quantize the weights of a neural network by using rescaling invariance property [Neyshabur et al., 2015].

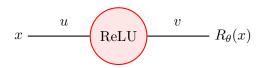


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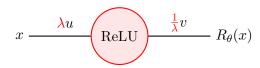
We keep one neuron where

- $\bullet \ \theta = (u, v) \in \mathbb{R}^{d_{\mathsf{in}} + d_{\mathsf{out}}}$
- $R_{\theta}: x \in \mathbb{R}^{d_{\mathsf{in}}} \mapsto \mathrm{ReLU}(\langle u, x \rangle) v = \mathbb{1}_{\langle u, x \rangle > 0} u v^{\top} x \in \mathbb{R}^{d_{\mathsf{out}}}$



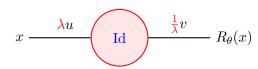
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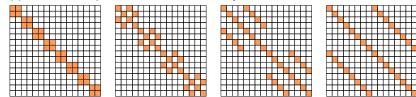
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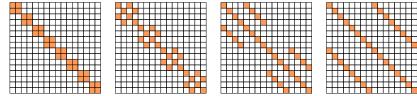
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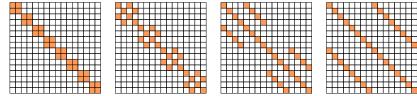
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- Butterfly matrices appear in factorization of dense matrices,
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 - ⇒ Quantization of complex rank-one matrices to quantize butterfly matrices and see the impact on the FFT.

Quantization of complex rank-one matrices

$$\forall \lambda \in \mathbb{C}^*, \ (\lambda x) \left(\frac{1}{\overline{\lambda}}y\right)^H$$

Complex-valued rank-one matrices

Problem formulation

Given $(x,y) \in \mathbb{C}^m \times \mathbb{C}^n$ and letting $\mathbb{CF}_t := \mathbb{F}_t + i\mathbb{F}_t$ (with \mathbb{F}_t : floats with t-bit significand), we want to solve:

$$x^*, y^* \in \arg\min_{\hat{x} \in \mathbb{CF}_t^m, \hat{y} \in \mathbb{CF}_t^n} ||xy^H - \hat{x}\hat{y}^H||^2$$

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Potential approaches

- Naive: Map x and y to their nearest neighbor in \mathbb{CF}_t with $\mathrm{round}(\cdot)$.
- **Real-valued:** Use optimal quantization algorithm for *real-valued* rank-one matrices [Gribonval et al., 2023].

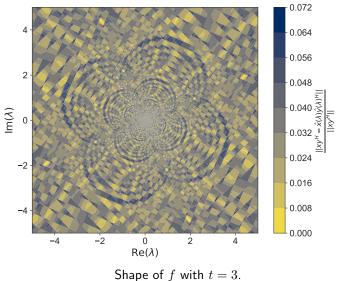
Problem resolution

Lemma: problem characterization

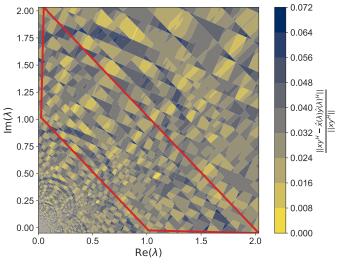
$$\inf_{\hat{\boldsymbol{x}} \in \mathbb{CF}_t^m, \hat{\boldsymbol{y}} \in \mathbb{CF}_t^n} \lVert \boldsymbol{x} \boldsymbol{y}^H - \hat{\boldsymbol{x}} \hat{\boldsymbol{y}}^H \rVert^2 = \inf_{\boldsymbol{\lambda} \in \mathbb{C}} f(\boldsymbol{\lambda})$$

where λ is the scaling parameter.

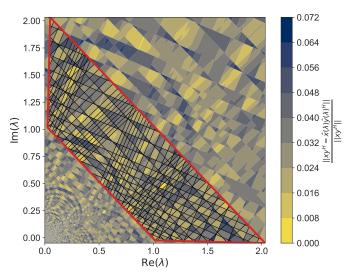
 \rightarrow Reduction of a problem with 4mn variables to a one scalar problem.



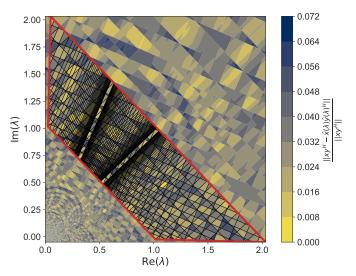
Shape of f with t=3



Shape of f with t=3.



Shape of f with t = 3 with $b \le 3$ (cf. Lemma 2)



Shape of f with t = 3 with $b \le 7$ (cf. Lemma 2)

Definition of the algorithm

• Introduction of a parameter $b_m \in \mathbb{N}$ to control the number of discontinuity lines.

Definition of the algorithm

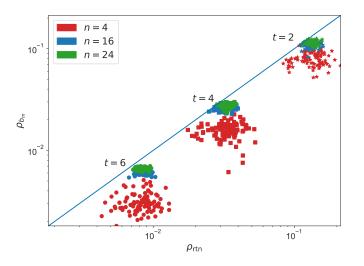
- Introduction of a parameter $b_m \in \mathbb{N}$ to control the number of discontinuity lines.
- Algorithm steps:
 - compute all the centroids from the discontinuity lines
 - $oldsymbol{2}$ evaluate f on all these centroids
 - **3** keep the **best** scaling factor, λ_{b_m}
 - \bullet return $\hat{x}_{b_m} := \operatorname{round}(\lambda_{b_m} x)$ and $\hat{y}_{b_m} := \operatorname{round}(\mu_{b_m} y)$

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Evaluation metric:
$$\rho := \frac{\|xy^H - \hat{x}\hat{y}^H\|}{\|xy^H\|}$$

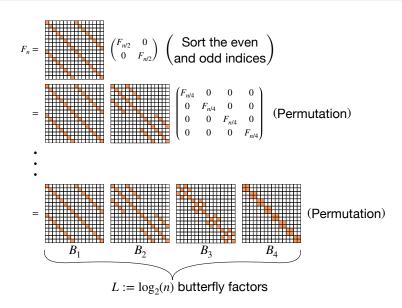
Results with 100 pairs $x, y \in \mathbb{C}^n$



 ρ_{b_m} in terms of $\rho_{\rm rtn}$ for different values of n and t with $b_m=3$.

Application to butterfly matrices

What's FFT?



New problem formulation

Consider $B_1,...,B_L \in \mathbb{C}^{n \times n}$. The new quantization problem is

$$B_1^*, ..., B_L^* \in \arg\min_{\hat{B}_1, ..., \hat{B}_L \in \mathbb{C}^{n \times n}} ||B_1 \cdots B_L - \hat{B}_1 \cdots \hat{B}_L||$$

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Heuristic for the parenthesis decomposition

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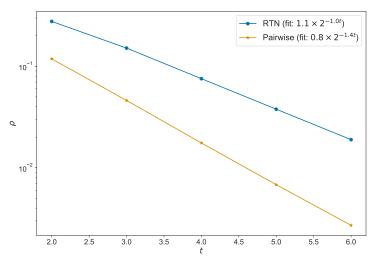
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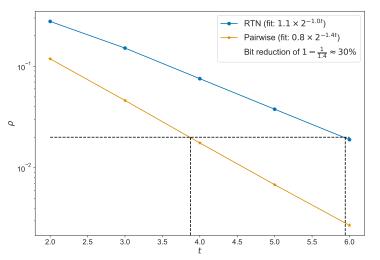
The metric is
$$\rho := \frac{\|B_1 \cdots B_L - \hat{B}_1 \cdots \hat{B}_L\|}{\|B_1 \cdots B_L\|}$$

Quantization error on the butterfly decomposition



Average on 10 gaussian matrices of ρ in terms of t with n=256 and $b_m=3$.

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Quantization error on the FFT

Let

- $x \in \mathbb{R}^n$ be the signal
- $y := Fx = B_1 \cdots B_L x \in \mathbb{C}^n$ its Fourier transform
- $\hat{y} := \hat{F}x = \hat{B}_1 \cdots \hat{B}_L x$
- $ho_{
 m fft} := rac{\|y \hat{y}\|}{\|y\|}$ the comparison metric

Quantization error on the FFT

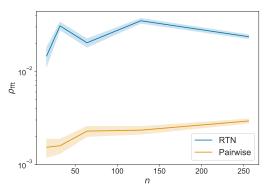
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the comparison metric



Average on 10 gaussian signals of ρ_{fft} in terms of n with t=5 and $b_m=3$.

Conclusion

Wrap-up:

- High-performance complex-valued rank-one quantization algorithm
- \bullet Compared to RTN, the number of bits is reduced by 30% for a given precision on butterfly matrices

What's next?

- Working on an extended version
- Quantization of a product of matrices of any rank
- Extend this work to quantize ReLU networks

Thanks for your attention

Références

- [1] B. Neyshabur, R. Tomioka, and N. Srebro. Norm-based capacity control in neural networks. In *Conference on learning theory*, pages 1376–1401. PMLR, 2015.
- [2] R. Gribonval, T. Mary, and E. Riccietti. Optimal quantization of rank-one matrices in floating-point arithmetic—with applications to butterfly factorizations. 2023.
- [3] J. W. Cooley and J. W. Tukey. An algorithm for the machine calculation of complex fourier series. *Mathematics of computation*, 19 (90):297–301, 1965.

Appendix: on Lemma 1 and Lemma 2

Expression of f

$$f: \lambda \in \mathbb{C} \mapsto \max_{\hat{x} \in \text{round}(\lambda x)} ||xy^H - \hat{x} \text{ round}(\mu(\hat{x})y)^H||$$

where $\mu(\hat{x}) := \frac{\langle x, \hat{x} \rangle}{\|x\|^2}$ if $x \neq 0$ and 0 otherwise.

Lemma: Discontinuity points of f

Let $x \in \mathbb{C}^m$. For each $x_j := u + iv$, j = 1, ..., m, the discontinuity points of the function $\lambda \in \Omega \mapsto \operatorname{round}(\lambda x_j)$ have for equations

$$\begin{cases} u \overline{\operatorname{Im}(\lambda)} = -v \operatorname{Re}(\lambda) + (k + \frac{1}{2}) 2^{2-b-t} \\ v \overline{\operatorname{Im}(\lambda)} = u \operatorname{Re}(\lambda) + (k + \frac{1}{2}) 2^{2-b-t} \\ v \overline{\operatorname{Im}(\lambda)} = u \operatorname{Re}(\lambda) - (k + \frac{1}{2}) 2^{2-b-t} \end{cases} \quad \forall k \in [2^{t-1}, 2^t - 1], \forall b \in \mathbb{N}$$

Appendix: more results

Proposition: on the infimum of f

We can prove that:

- *f* is continuous on the accumulation lines.
- ullet f admits a minimizer on $\mathbb C.$