

Compression in the Space of Permutations

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Abstract—We investigate lossy compression (source coding) of data in the form of permutations. This problem has direct applications in the storage of ordinal data or rankings, and in the analysis of sorting algorithms. We analyze the rate-distortion characteristic for the permutation space under the uniform distribution, and the minimum achievable rate of compression that allows a bounded distortion after recovery. Our analysis is with respect to different practical and useful distortion measures, including Kendall tau distance, Spearman’s footrule, Chebyshev distance, and inversion- ℓ_1 distance. We establish equivalence of source code designs under certain distortions and show simple explicit code designs that incur low encoding/decoding complexities and are asymptotically optimal. Finally, we show that for the Mallows model, a popular nonuniform ranking model on the permutation space, both the entropy and the maximum distortion at zero rate are much lower than the uniform counterparts, which motivates the future design of efficient compression schemes for this model.

Index Terms—Lossy compressions, mallows model, partial sorting, permutation space.

I. INTRODUCTION

PERMUTATIONS are fundamental mathematical objects and the topic of *codes in permutations* is a well-studied subject in coding theory. A variety of applications that correspond to different metric functions on the symmetric group on n elements \mathcal{S}_n have been investigated. For example, some works focus on error-correcting codes in \mathcal{S}_n with Hamming distance [1], [2], and some others investigate the error correction problem under metrics such as Chebyshev distance [3] and Kendall tau distance [4].

While error correction problems in permutation spaces have been investigated before, the lossy compression problem is largely left unattended. In [5] and [6], the authors investigate

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the lossless compression of a group of permutations with certain properties, such as efficient rank querying (given an element, get its rank in the permutation) and selection (given a rank, retrieve the corresponding element). By contrast, in this paper we consider the lossy compression (source coding) of permutations, which is motivated by the problems of storing ranking data, and lower bounding the complexity of approximate sorting, which we now describe.

A. Storing Ranking Data

In applications such as recommendation systems, users rank products and these rankings are analyzed to provide new recommendations. To have personalized recommendations, it may be necessary to store the ranking data for each user in the system, and hence the storage efficiency of ranking data is of interest. Because a ranking of n items can be represented as a permutation of 1 to n , storing a ranking is equivalent to storing a permutation. Furthermore, in many cases a rough knowledge of the ranking (e.g., finding one of the top five elements instead of the top element) is sufficient. This poses the question of the number of bits needed for permutation storage when a certain amount of error can be tolerated. In many current applications the cost of lossless storage is usually tolerable and hence lossy compression may not be necessary. However lossy compression is a fundamental topic and it is of theoretical interest to understand the trade-off involved.

B. Lower Bounding the Complexity of Approximate Sorting

Given a group of elements of distinct values, comparison-based sorting can be viewed as the process of searching for a true ranking by pairwise comparisons. Since each comparison in sorting provides at most 1 bit of information, the log-size of the permutation set \mathcal{S}_n , $\log_2(n!)$, provides a lower bound to the required number of comparisons. Similarly, the lossy source coding of permutations provides a lower bound on the number of comparisons to the problem of comparison-based approximate sorting, which can be seen as finding a true permutation up to a certain distortion. Again, the log-size of the code indicates the amount of information (in bits) needed to specify the true permutation, which in turn provides a lower bound on the number of pairwise comparisons needed.

In one line of work, authors of [7] derived both lower and upper bounds for approximate sorting in some range of allowed distortion with respect to the Spearman’s footrule metric [8] (see Definition 1 below). Another line of work concerns an important class of approximate sorting, the problem of *partial sorting*, first proposed in [9] (cf. [10, Ch. 8] for

an exposition on the relationships between various sorting problems). Given a set of n elements \mathcal{V} and a set of indices $\mathcal{I} \subset \{1, 2, \dots, n\}$, a partial sorting algorithm aims to arrange the elements into a list $[v_1, v_2, \dots, v_n]$ such that for any $i \in \mathcal{I}$, all elements with indices $j < i$ are no greater than v_i , and all elements with indices $j' > i$ are no smaller than v_i . A partial sorting algorithm essentially selects all elements with ranks in the set \mathcal{I} , and hence is also called *multiple selection*. The information-theoretic lower bound for partial sorting algorithms have been proposed in [11], and the authors of [12] propose a multiple selection algorithms with expected number of comparisons within the information-theoretic lower-bound and an asymptotically negligible additional term.

Comparing with existing work (such as [11]), our analysis framework via rate-distortion theory is more general as we provide an information-theoretic lower bound on the query complexity for *all* approximate sorting algorithms that achieve a certain distortion, and the multiple selection algorithm proposed in [12] turns out to be optimal for the general approximate sorting problem as well. Therefore, our information-theoretic lower bound is tight.

Remark 1 (Comparison-Based Sorting Implies Compression): It is worth noting that every comparison-based sorting algorithm corresponds to a compression scheme of the permutation space. In particular, the string of bits that represent comparison outcomes in any deterministic (approximate) sorting algorithm corresponds to a (lossy) representation of the permutation.

For a more in-depth discussion on the relationship between sorting and compression, see [13] and references therein.

Beyond the above applications, the rate-distortion theory in permutation spaces is of technical interest on its own because the permutation space does not possess the product structure that a discrete memoryless source induces.

With the above motivations, we consider the problem of lossy compression in permutation spaces in this paper. Following the classical rate-distortion formulation, we aim to determine, given a distortion measure $d(\cdot, \cdot)$, the minimum number of bits needed to describe a permutation with distortion at most D .

The analysis of the lossy compression problem depends on the source distribution and the distortion measure. We are mainly concerned with the permutation spaces with a uniform distribution, and consider different distortion measures based on four distances in the permutation spaces: the Kendall tau distance, Spearman's footrule, Chebyshev distance and inversion- ℓ_1 distance. As we shall see in Section II, each of these distortion measures (except inversion- ℓ_1 distance¹) has its own operational meaning that may be useful in different applications.

In addition to characterizing the trade-off between rate and distortion, we also show that under the uniform distribution over the permutation space, there are close relationships between some of the distortion measures of interest

¹We are interested in inversion- ℓ_1 distance due to its extremal property shown in Equation (7), which is useful when we derive results for other permutation spaces. Further use of this metric in the context of smooth representation of permutations can be found in [14].

in this paper. We use these relations to establish the corresponding equivalence of source codes in permutation spaces with different distortion measures. For each distortion measure, we provide simple and constructive achievability schemes, leading to explicit code designs with low complexity.

Finally, we turn our attention to non-uniform distributions over the permutation space. In some applications, we may have prior knowledge about the permutation data, which can be captured in a model of non-uniform distribution. There are a variety of distributional models in different contexts, such as the Bradley-Terry model [15], the Luce-Plackett model [16], [17], and the Mallows model [18]. Among these, we choose the Mallows model due to its richness and applicability in various ranking applications [19]–[21]. We analyze the lossless and lossy compression of the permutation space under the Mallows model and with the Kendall tau distance as the distortion measure, and characterize its entropy and end points of its rate-distortion function.

The rest of the paper is organized as follows. We first present the problem formulation in Section II. We then analyze the geometry of the permutation spaces and show that there exist close relationships between some distortion measures of interest in this paper in Section III. In Section IV, we derive the rate-distortion functions for different permutation spaces. In Section V, we provide achievability schemes for different permutation spaces under different regimes. After that, we turn our attention to non-uniform distributional model over the permutation space and analyze the lossless and lossy compression for Mallows model in Section VI. We conclude with a few remarks in Section VII.

II. PROBLEM FORMULATION

In this section we discuss aspects of the formulation of the rate-distortion problem for permutation spaces. We first introduce the distortion measures of interest in Section II-B, and then provide a mathematical formulation of the rate-distortion problem in Section II-C.

A. Notation and Facts

Let \mathcal{S}_n denote the symmetric group of n elements. We write an element of \mathcal{S}_n as an array of natural numbers with values ranging from $1, \dots, n$ and every value occurring only once in the array. For example, $\sigma = [3, 4, 1, 2, 5] \in \mathcal{S}_5$. This is also known as the *vector notation* for permutations. The identity of the symmetric group \mathcal{S}_n (identity permutation) is denoted by $\text{Id} = [1, 2, \dots, n]$. For a permutation σ , we denote its permutation inverse by σ^{-1} , where $\sigma^{-1}(x) = i$ when $\sigma(i) = x$, and $\sigma(i)$ is the i -th element in array σ . For example, the permutation inverse of $\sigma = [2, 5, 4, 3, 1]$ is $\sigma^{-1} = [5, 1, 4, 3, 2]$. Given a metric $d : \mathcal{S}_n \times \mathcal{S}_n \rightarrow \mathbb{R}^+ \cup \{0\}$, we define a *permutation space* $\mathcal{X}(\mathcal{S}_n, d)$.

Throughout the paper, we let $[a : b] \triangleq \{a, a + 1, \dots, b - 1, b\}$ for any two integers a and b , and use $\sigma[a : b]$ as a shorthand for the vector $[\sigma(a), \sigma(a + 1), \dots, \sigma(b)]$.

We make use of the following version of *Stirling's approximation*:

$$\left(\frac{m}{e}\right)^m e^{\frac{1}{12m+1}} < \frac{m!}{\sqrt{2\pi m}} < \left(\frac{m}{e}\right)^m e^{\frac{1}{12m}}, \quad m \geq 1. \quad (1)$$

B. Distortion Measures

There exists many natural distortion measures on the permutation group \mathcal{S}_n [22]. In this paper we choose a few distortion measures of interest in a variety of application settings, including Spearman's footrule (ℓ_1 distance between two permutation vectors), Chebyshev distance (ℓ_∞ distance between two permutation vectors), Kendall tau distance and the inversion- ℓ_1 distance (see Definition 5).

Before introducing definitions for these distortion measures, we define the concept of *ranking*. Given a list of items with values v_1, v_2, \dots, v_n such that $v_{\sigma^{-1}(1)} \succ v_{\sigma^{-1}(2)} \succ \dots \succ v_{\sigma^{-1}(n)}$, where $a \succ b$ indicates a is preferred to b , we say the permutation σ is the *ranking* of this list of items, where $\sigma(i)$ provides the rank of item i , and $\sigma^{-1}(r)$ provides the index of the item with rank r . Note that sorting via pairwise comparisons is simply the procedure of rearranging v_1, v_2, \dots, v_n to $v_{\sigma^{-1}(1)}, v_{\sigma^{-1}(2)}, \dots, v_{\sigma^{-1}(n)}$ based on preferences obtained from pairwise comparisons.

Given two rankings σ_1 and σ_2 , we measure the total deviation of ranking and maximum deviation of ranking by the Spearman's footrule and the Chebyshev distance respectively.

Definition 1 (Spearman's Footrule [8]): Given two permutations $\sigma_1, \sigma_2 \in \mathcal{S}_n$, the Spearman's footrule between σ_1 and σ_2 is

$$d_{\ell_1}(\sigma_1, \sigma_2) \triangleq \|\sigma_1 - \sigma_2\|_1 = \sum_{i=1}^n |\sigma_1(i) - \sigma_2(i)|.$$

Definition 2 (Chebyshev Distance): Given two permutations $\sigma_1, \sigma_2 \in \mathcal{S}_n$, the Chebyshev distance between σ_1 and σ_2 is

$$d_{\ell_\infty}(\sigma_1, \sigma_2) \triangleq \|\sigma_1 - \sigma_2\|_\infty = \max_{1 \leq i \leq n} |\sigma_1(i) - \sigma_2(i)|.$$

The Spearman's footrule in \mathcal{S}_n is upper bounded by $\lfloor n^2/2 \rfloor$ (cf. Table I) and the Chebyshev distance in \mathcal{S}_n is upper bounded by $n - 1$.

Given two lists of items with ranking σ_1 and σ_2 , let $\pi_1 \triangleq \sigma_1^{-1}$ and $\pi_2 \triangleq \sigma_2^{-1}$, then we define the number of pairwise adjacent swaps on π_1 that changes the ranking of π_1 to the ranking of π_2 as the Kendall tau distance.

Definition 3 (Kendall Tau Distance [23]): The Kendall tau distance $d_\tau(\sigma_1, \sigma_2)$ from one permutation σ_1 to another permutation σ_2 is defined as the minimum number of transpositions of pairwise adjacent elements required to change σ_1 into σ_2 .

The Kendall tau distance is upper bounded by $\binom{n}{2}$.

Example 1 (Kendall Tau Distance): The Kendall tau distance for $\sigma_1 = [1, 5, 4, 2, 3]$ and $\sigma_2 = [3, 4, 5, 1, 2]$ is $d_\tau(\sigma_1, \sigma_2) = 7$, as one needs at least 7 transpositions of pairwise adjacent elements to change σ_1 to σ_2 . For example,

$$\begin{aligned} \sigma_1 &= [1, 5, 4, 2, 3] \\ &\rightarrow [1, 5, 4, \mathbf{3}, 2] \rightarrow [1, \mathbf{5}, \mathbf{3}, 4, 2] \rightarrow [\mathbf{1}, \mathbf{3}, 5, 4, 2] \\ &\rightarrow [3, \mathbf{1}, 5, 4, 2] \rightarrow [3, 5, \mathbf{1}, 4, 2] \rightarrow [3, \mathbf{5}, \mathbf{4}, 1, 2] \\ &\rightarrow [3, 4, 5, 1, 2] = \sigma_2. \end{aligned}$$

Being a popular global measure of disarray in statistics, Kendall tau distance also has a natural connection to sorting algorithms. In particular, given a list of items with values

v_1, v_2, \dots, v_n such that $v_{\sigma^{-1}(1)} \succ v_{\sigma^{-1}(2)} \succ \dots \succ v_{\sigma^{-1}(n)}$, $d_\tau(\sigma^{-1}, \text{Id})$ is the number of swaps needed to sort this list of items in a bubble-sort algorithm [24].

Finally, we introduce a distortion measure based on the concept of inversion vector, another measure of the order-ness of a permutation.

Definition 4 (Inversion, Inversion Vector [25]): An inversion in a permutation $\sigma \in \mathcal{S}_n$ is a pair $(\sigma(i), \sigma(j))$ such that $i < j$ and $\sigma(i) > \sigma(j)$.

We use $I_n(\sigma)$ to denote the total number of inversions in $\sigma \in \mathcal{S}_n$, and

$$K_n(k) \triangleq |\{\sigma \in \mathcal{S}_n : I_n(\sigma) = k\}| \quad (2)$$

to denote the number of permutations with k inversions.

Denote $i' = \sigma(i)$ and $j' = \sigma(j)$, then $i = \sigma^{-1}(i')$ and $j = \sigma^{-1}(j')$, and thus $i < j$ and $\sigma(i) > \sigma(j)$ is equivalent to $\sigma^{-1}(i') < \sigma^{-1}(j')$ and $i' > j'$.

A permutation $\sigma \in \mathcal{S}_n$ is associated with an inversion vector $\mathbf{x}_\sigma \in \mathcal{G}_n \triangleq [0 : 1] \times [0 : 2] \times \dots \times [0 : n - 1]$, where $\mathbf{x}_\sigma(i')$, $1 \leq i' \leq n - 1$ is the number of inversions in σ in which $i' + 1$ is the first element. Formally, for $i' = 2, \dots, n$,

$$\mathbf{x}_\sigma(i' - 1) = \left| \left\{ j' \in [1 : n] : j' < i', \sigma^{-1}(j') > \sigma^{-1}(i') \right\} \right|.$$

Let $\pi \triangleq \sigma^{-1}$, then the inversion vector of π , \mathbf{x}_π , measures the deviation of ranking σ from Id. In particular, note that

$$\begin{aligned} \mathbf{x}_\pi(k) &= \left| \left\{ j' \in [1 : n] : j' < k, \pi^{-1}(j') > \pi^{-1}(k) \right\} \right| \\ &= \left| \left\{ j' \in [1 : n] : j' < k, \sigma(j') > \sigma(k) \right\} \right| \end{aligned}$$

indicates the number of elements that have *larger ranks* and *smaller item indices* than that of the element with index k . In particular, the rank of the element with index n is $n - \mathbf{x}_\pi(n - 1)$.

Example 2: Given 5 items such that $v_4 \succ v_1 \succ v_2 \succ v_5 \succ v_3$, then the inverse of the ranking permutation is $\pi = [4, 1, 2, 5, 3]$, with inversion vector $\mathbf{x}_\pi = [0, 0, 3, 1]$. Therefore, the rank of the v_5 is $n - \mathbf{x}_\pi(n - 1) = 5 - 1 = 4$.

The mapping from \mathcal{S}_n to \mathcal{G}_n is one-to-one as the inversion vectors exactly describes the execution of the algorithm insertion sort [24].

With these, we define the inversion- ℓ_1 distance.

Definition 5 (Inversion- ℓ_1 Distance): Given two permutations $\sigma_1, \sigma_2 \in \mathcal{S}_n$, we define the inversion- ℓ_1 distance, ℓ_1 distance of two inversion vectors, as

$$d_{\mathbf{x}, \ell_1}(\sigma_1, \sigma_2) \triangleq \sum_{i=1}^{n-1} |\mathbf{x}_{\sigma_1}(i) - \mathbf{x}_{\sigma_2}(i)|. \quad (3)$$

Example 3 (Inversion- ℓ_1 Distance): The inversion vector for permutation $\sigma_1 = [1, 5, 4, 2, 3]$ is $\mathbf{x}_{\sigma_1} = [0, 0, 2, 3]$, as the inversions are (4, 2), (4, 3), (5, 4), (5, 2), (5, 3). The inversion vector for permutation $\sigma_2 = [3, 4, 5, 1, 2]$ is $\mathbf{x}_{\sigma_2} = [0, 2, 2, 2]$, as the inversions are (3, 1), (3, 2), (4, 1), (4, 2), (5, 1), (5, 2). Therefore,

$$d_{\mathbf{x}, \ell_1}(\sigma_1, \sigma_2) = d_{\ell_1}([0, 0, 2, 3], [0, 2, 2, 2]) = 3.$$

As we shall see in Section III, all these distortion measures are related. While the operational significance of the

inversion- ℓ_1 distance may not be as clear as other distortion measures, some of its properties provide useful insights in the analysis of other distortion measures.

Remark 2: While Spearman's footrule and Chebyshev distance operate on the ranking domain, inversion vector and Kendall tau distance can be viewed as operating on the inverse of the ranking domain.

C. Rate-Distortion Problems

With the distortions defined in Section II-B, in this section we define rate-distortion problems under both average-case and worst-case distortions.

Definition 6 (Codebook for Average-Case Distortion): An (n, D_n) source code $\tilde{\mathcal{C}}_n \subseteq \mathcal{S}_n$ for $\mathcal{X}(\mathcal{S}_n, d)$ under the average-case distortion is a set of permutations such that for a σ that is drawn from \mathcal{S}_n according to a distribution P on \mathcal{S}_n , there exists an encoding mapping $f_n : \mathcal{S}_n \rightarrow \tilde{\mathcal{C}}_n$ that

$$\mathbb{E}_P [d(f_n(\sigma), \sigma)] \leq D_n. \quad (4)$$

The mapping $f_n : \mathcal{S}_n \rightarrow \tilde{\mathcal{C}}_n$ can be assumed to satisfy

$$f_n(\sigma) = \arg \min_{\sigma' \in \tilde{\mathcal{C}}_n} d(\sigma', \sigma)$$

for any $\sigma \in \mathcal{S}_n$.

In most parts of this paper we focus on the case P is uniformly distributed over the symmetric group \mathcal{S}_n , except in Section VI, where a distribution arising from the Mallows model is used. In both cases the source distribution has support \mathcal{S}_n , and we define the worst-case distortion as follows.

Definition 7 (Codebook for Worst-Case Distortion): An (n, D_n) source code $\hat{\mathcal{C}}_n \subseteq \mathcal{S}_n$ for $\mathcal{X}(\mathcal{S}_n, d)$ under the worst-case distortion is a set of permutations such that for any $\sigma \in \mathcal{S}_n$, there exists an encoding mapping $f_n : \mathcal{S}_n \rightarrow \hat{\mathcal{C}}_n$ that

$$\max_{\sigma \in \mathcal{S}_n} d(f_n(\sigma), \sigma) \leq D_n. \quad (5)$$

The mapping $f_n : \mathcal{S}_n \rightarrow \hat{\mathcal{C}}_n$ can be assumed to satisfy

$$f_n(\sigma) = \arg \min_{\sigma' \in \hat{\mathcal{C}}_n} d(\sigma', \sigma)$$

for any $\sigma \in \mathcal{S}_n$.

Definition 8 (Rate Function): For a class of source codes $\{\mathcal{C}_n\}$ that achieve a distortion D_n , let $A(n, D_n)$ be the minimum size of such codes, and we define the minimal rate for distortions D_n as

$$R(D_n) \triangleq \frac{\log A(n, D_n)}{\log n!}.$$

In particular, we denote the minimum rate of the codebook under average-case distortion with uniform source distribution and worst-case distortions by $\tilde{R}(D_n)$ and $\hat{R}(D_n)$ respectively.

Similar to the classical rate-distortion setup, we are interested in deriving the trade-off between distortion level D_n and the rate $R(D_n)$ as $n \rightarrow \infty$. In this work we show that for the distortions $d(\cdot, \cdot)$ and the sequences of distortions $\{D_n, n \in \mathbb{Z}^+\}$ of interest, $\lim_{n \rightarrow \infty} R(D_n)$ exists.

For Kendall tau distance and inversion- ℓ_1 distance, a close observation shows that in regimes such as $D_n = O(n)$ and $D_n = \Theta(n^2)$, $\lim_{n \rightarrow \infty} R(D_n) = 1$ and $\lim_{n \rightarrow \infty} R(D_n) = 0$ respectively. In these two regimes, the trade-off between rate and distortion is really shown in the higher order terms in $\log A(n, D_n)$, i.e.,

$$r(D_n) \triangleq \log A(n, D_n) - \log n! \lim_{n \rightarrow \infty} R(D_n). \quad (6)$$

For convenience, we categorize the distortion D_n under Kendall tau distance or inversion- ℓ_1 distance into three regimes. We say D is small when $D = O(n)$, moderate when $D = \Theta(n^{1+\delta})$, $0 < \delta < 1$, and large when $D = \Theta(n^2)$.²

We choose to omit the higher order term analysis for $\mathcal{X}(\mathcal{S}_n, d_{\ell_1})$ because its analysis is essentially the same as $\mathcal{X}(\mathcal{S}_n, d_\tau)$, and the analysis for $\mathcal{X}(\mathcal{S}_n, d_{\ell_\infty})$ is still open.

Note that the higher order terms $r(D_n)$ may behave differently under average and worst-case distortions, and in this paper we restrict our attention to the worst-case distortion.

III. RELATIONSHIPS BETWEEN DISTORTION MEASURES

In this section we show how the four distortion measures defined in Section II-B are related to each other, which is summarized in (7) and (8). These relationships imply equivalence in some lossy compression schemes, which we exploit to derive the rate-distortion functions in Section IV.

For any $\sigma_1 \in \mathcal{S}_n$ and σ_2 randomly uniformly chosen from \mathcal{S}_n , the following relations hold:

$$\begin{aligned} nd_{\ell_\infty}(\sigma_1, \sigma_2) &\geq d_{\ell_1}(\sigma_1, \sigma_2) \\ &\geq d_\tau(\sigma_1^{-1}, \sigma_2^{-1}) \\ &\geq d_{\mathbf{x}, \ell_1}(\sigma_1^{-1}, \sigma_2^{-1}), \end{aligned} \quad (7)$$

$$\begin{aligned} nd_{\ell_\infty}(\sigma_1, \sigma_2) &\stackrel{w.h.p.}{\lesssim} d_{\ell_1}(\sigma_1, \sigma_2) \\ &\lesssim d_\tau(\sigma_1^{-1}, \sigma_2^{-1}) \\ &\stackrel{w.h.p.}{\lesssim} d_{\mathbf{x}, \ell_1}(\sigma_1^{-1}, \sigma_2^{-1}), \end{aligned} \quad (8)$$

where $x \lesssim y$ indicates $x < c \cdot y$ for some constant $c > 0$, and $\stackrel{w.h.p.}{\lesssim}$ indicates \lesssim with high probability.

Next, we provide detailed arguments for (7) and (8) by analyzing the relationship between different pairs of distortion measures.

1) *Spearman's Footrule and Chebyshev Distance:* Let σ_1 and σ_2 be any permutations in \mathcal{S}_n , then by definition,

$$d_{\ell_1}(\sigma_1, \sigma_2) \leq n \cdot d_{\ell_\infty}(\sigma_1, \sigma_2), \quad (9)$$

and additionally, a scaled Chebyshev distance lower bounds the Spearman's footrule with high probability. More specifically, for any $\pi \in \mathcal{S}_n$, let σ be a permutation chosen uniformly from \mathcal{S}_n , then

$$\mathbb{P}[c_1 \cdot n \cdot d_{\ell_\infty}(\pi, \sigma) \leq d_{\ell_1}(\pi, \sigma)] \geq 1 - O(1/n) \quad (10)$$

for any positive constant $c_1 < 1/3$ (See Appendix A-A for proof).

²In the small distortion region with $R(D_n) = 1$, $r(D_n)$ is negative while in the large distortion region where $R(D_n) = 0$, $r(D_n)$ is positive.

TABLE I
CHARACTERIZATION OF MAXIMUM, MEAN AND
VARIANCE OF VARIOUS DISTANCES

	Max	Mean	Variance
$n \cdot \ell_\infty$	$n(n-1)$	$< n^2$	$\Theta(n^3)$
ℓ_1	$\lfloor n^2/2 \rfloor$	$n^2/3 + o(n^2)$	$2n^3/45 + o(n^3)$
Kendall-tau	$n(n-1)/2$	$n^2/4 + o(n^2)$	$n^3/36 + o(n^3)$
inversion- ℓ_1	$n(n-1)/2$	$> n^2/8$	$< n^3/6$

2) *Spearman's Footrule and Kendall Tau Distance*: The following theorem is a well-known result on the relationship between the Kendall tau distance and the ℓ_1 distance of permutation vectors.

Theorem 1 [8]: Let σ_1 and σ_2 be any permutations in \mathcal{S}_n , then

$$d_{\ell_1}(\sigma_1, \sigma_2)/2 \leq d_\tau(\sigma_1^{-1}, \sigma_2^{-1}) \leq d_{\ell_1}(\sigma_1, \sigma_2). \quad (11)$$

3) *Inversion- ℓ_1 Distance and Kendall Tau Distance*: We show that the inversion- ℓ_1 distance and the Kendall tau distance are related via Theorem 2.

Theorem 2: Let σ_1 and σ_2 be any permutations in \mathcal{S}_n , then for $n \geq 2$,

$$\frac{1}{n-1} d_\tau(\sigma_1, \sigma_2) \leq d_{\mathbf{x}, \ell_1}(\mathbf{x}_{\sigma_1}, \mathbf{x}_{\sigma_2}) \leq d_\tau(\sigma_1, \sigma_2). \quad (12)$$

Proof: See Appendix A-B. ■

Remark 3: The lower and upper bounds in Theorem 2 are tight in the sense that there exist permutations σ_1 and σ_2 that satisfy the equality in either lower or upper bound. For equality in lower bound, when $n = 2m$, let $\sigma_1 = [1, 3, 5, \dots, 2m-3, 2m-1, 2m, 2m-2, \dots, 6, 4, 2]$, $\sigma_2 = [2, 4, 6, \dots, 2m-2, 2m, 2m-1, 2m-3, \dots, 5, 3, 1]$, then $d_\tau(\sigma_1, \sigma_2) = n(n-1)/2$ and $d_{\mathbf{x}, \ell_1}(\sigma_1, \sigma_2) = n/2$, as $\mathbf{x}_{\sigma_1} = [0, 0, 1, 1, 2, 2, \dots, m-2, m-2, m-1, m-1]$, $\mathbf{x}_{\sigma_2} = [0, 1, 1, 2, 2, 3, \dots, m-2, m-1, m-1, m]$. For equality in upper bound, note that $d_\tau(\text{Id}, \sigma) = d_{\mathbf{x}, \ell_1}(\text{Id}, \sigma)$.

Theorem 2 shows that in general $d_\tau(\sigma_1, \sigma_2)$ is not a good approximation to $d_{\mathbf{x}, \ell_1}(\sigma_1, \sigma_2)$ due to the $1/(n-1)$ factor. However, (13) shows that Kendall tau distance scaled by a constant actually provides a lower bound to the inversion- ℓ_1 distance with high probability. In particular, for any $\pi \in \mathcal{S}_n$, let σ be a permutation chosen uniformly from \mathcal{S}_n , then

$$\mathbb{P}[c_2 \cdot d_\tau(\pi, \sigma) \leq d_{\mathbf{x}, \ell_1}(\pi, \sigma)] \geq 1 - O(1/n) \quad (13)$$

for any positive constant $c_2 < 1/2$ (See Appendix A-C for proof).

Results in both (10) and (13) are concentration results in the sense that the mean for distances are $\Theta(n^2)$ and the standard deviation for the distances are $\Theta(n^{3/2})$. Related quantities are summarized in Table I, where results on ℓ_1 distance and Kendall tau distance are from [8, Table 1], and results on ℓ_∞ distance and inversion- ℓ_1 distance are derived in Appendix A-A and Appendix A-C. Therefore, these distance are concentrated around mean and separated probabilistically.

Remark 4: The constants in (10) and (13) may be improved if both of the permutations in question are chosen randomly, instead of one being fixed. However as the techniques are exactly same, we refrain from providing those expressions.

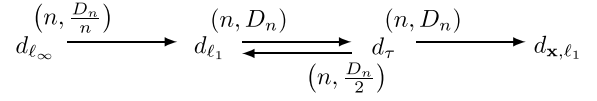


Fig. 1. Relationship between source codes. An arrow indicates a source code in one space implies a source in another space.

IV. TRADE-OFFS BETWEEN RATE AND DISTORTION

In this section we present some of the main results of this paper—the trade-offs between rate and distortion in permutation spaces. Throughout this section we assume the permutations are uniformly distributed over \mathcal{S}_n .

We first present Theorem 3, which shows how a lossy source code under one distortion measure implies a lossy source code under another distortion measure. Building on these relationships, Theorem 4 shows that all distortion measures in this paper essentially share the same rate-distortion function. Last, in Section IV-B, we present results on the trade-off between rate and distortion for $\mathcal{X}(\mathcal{S}_n, d_\tau)$ and $\mathcal{X}(\mathcal{S}_n, d_{\mathbf{x}, \ell_1})$ when the distortion leads to degenerate rates $R(D_n) = 0$ and $R(D_n) = 1$.

A. Rate-Distortion Functions

Theorem 3 (Relationships of Lossy Source Codes): For both worst-case distortion and average-case distortion with uniform distribution, a following source code on the left hand side implies a source code on the right hand side:

- 1) $(n, D_n/n)$ source code for $\mathcal{X}(\mathcal{S}_n, d_{\ell_\infty}) \Rightarrow (n, D_n)$ source code for $\mathcal{X}(\mathcal{S}_n, d_{\ell_1})$,
- 2) (n, D_n) source code for $\mathcal{X}(\mathcal{S}_n, d_{\ell_1}) \Rightarrow (n, D_n)$ source code for $\mathcal{X}(\mathcal{S}_n, d_\tau)$,
- 3) (n, D_n) source code for $\mathcal{X}(\mathcal{S}_n, d_\tau) \Rightarrow (n, 2D_n)$ source code for $\mathcal{X}(\mathcal{S}_n, d_{\ell_1})$,
- 4) (n, D_n) source code for $\mathcal{X}(\mathcal{S}_n, d_\tau) \Rightarrow (n, D_n)$ source code for $\mathcal{X}(\mathcal{S}_n, d_{\mathbf{x}, \ell_1})$.

The relationship between source codes is summarized in Fig. 1.

Remark 5 (Non-Equivalence of Lossy Source Codes for $\mathcal{X}(\mathcal{S}_n, d_{\ell_1})$ and $\mathcal{X}(\mathcal{S}_n, d_{\ell_\infty})$): It is worth noting that in general, an (n, D_n) source code for $\mathcal{X}(\mathcal{S}_n, d_{\ell_1})$ does not imply an $(n, D_n/(nc_1) + O(1))$ source code for $\mathcal{X}(\mathcal{S}_n, d_{\ell_\infty})$ in spite of the relationship shown in (8), even under the average-case distortion. This is exemplified in Example 4 below.

In [26], it was shown incorrectly that lossy source codes for $\mathcal{X}(\mathcal{S}_n, d_{\ell_1})$ and $\mathcal{X}(\mathcal{S}_n, d_{\ell_\infty})$ are equivalent, leading to an over-generalized version of Theorem 3.

Example 4: When $n = km$ and $m = n^\delta$, we define the following k sets with size m

- $$\begin{aligned} \mathcal{I}_1 &= \{2, 3, \dots, m, m+1\}, \\ \mathcal{I}_2 &= \{m+2, m+3, \dots, 2m, 2m+1\}, \\ &\dots \\ \mathcal{I}_j &= \{(j-1)m+2, (j-1)m+3, \dots, jm, jm+1\}, \\ &\dots \\ \mathcal{I}_k &= \{(k-1)m+2, (k-1)m+3, \dots, n, 1\} \end{aligned}$$

and construct the following k subsequences for any permutation $\sigma \in \mathcal{S}_n$:

$$\mathbf{s}_j(\sigma) = [\sigma(j_1), \sigma(j_2), \dots, \sigma(j_m)], \quad 1 \leq j \leq k$$

where for each j , $j_p \in \mathcal{I}_j$ for any $1 \leq p \leq m$ and $j_1 < j_2 < \dots < j_m$.

Given any permutation σ , we can encode it as $\hat{\sigma}$ by sorting each of its subsequences $\mathbf{s}_j(\sigma)$, $1 \leq j \leq k$. Then the overall distortion $\mathcal{X}(\mathcal{S}_n, d_{\ell_1})$ satisfies

$$\begin{aligned} D_{\ell_1} &\leq (k-1)m^2/2 + [(m-1)^2 + 2n] = O(km^2/2) \\ &= O(n^{1+\delta}). \end{aligned}$$

Therefore, this source code is an (n, D_n) source code for $\mathcal{X}(\mathcal{S}_n, d_{\ell_1})$. However, for any σ in \mathcal{S}_n , if $\sigma(1) \neq 1$,

$$d_{\ell_\infty}(\sigma, \hat{\sigma}) \geq (k-1)m + 2 - 1 \geq (k-1)m = \Theta(n).$$

Hence this encoding achieves average distortion $\Theta(n)$ in $\mathcal{X}(\mathcal{S}_n, d_{\ell_\infty})$. Therefore, while this code is D_n for $\mathcal{X}(\mathcal{S}_n, d_{\ell_1})$, it is not D_n/n for $\mathcal{X}(\mathcal{S}_n, d_{\ell_\infty})$.

Similarly, one can find a code that achieves distortion $O(n^{1+\delta})$ for $\mathcal{X}(\mathcal{S}_n, d_{\mathbf{x}, \ell_1})$ but not $\mathcal{X}(\mathcal{S}_n, d_\tau)$.

The proof of Theorem 3 is based on the relationships between various distortion measures investigated in Section III and we defer the proof details in Appendix B-A.

Below shows that, for the uniform distribution on \mathcal{S}_n , the rate-distortion function is the same for both average- and worst-case, apart from the terms that are asymptotically negligible.

Theorem 4 (Rate-Distortion Functions): For permutation spaces $\mathcal{X}(\mathcal{S}_n, d_{\mathbf{x}, \ell_1})$, $\mathcal{X}(\mathcal{S}_n, d_\tau)$, and $\mathcal{X}(\mathcal{S}_n, d_{\ell_1})$,

$$\begin{aligned} \bar{R}(D_n) &= \hat{R}(D_n) \\ &= \begin{cases} 1 & \text{if } D_n = O(n), \\ 1 - \delta & \text{if } D_n = \Theta(n^{1+\delta}), \quad 0 < \delta \leq 1. \end{cases} \end{aligned}$$

For the permutation space $\mathcal{X}(\mathcal{S}_n, d_{\ell_\infty})$,

$$\begin{aligned} \bar{R}(D_n) &= \hat{R}(D_n) \\ &= \begin{cases} 1 & \text{if } D_n = O(1), \\ 1 - \delta & \text{if } D_n = \Theta(n^\delta), \quad 0 < \delta \leq 1. \end{cases} \end{aligned} \quad (14)$$

The rate-distortion functions for all these spaces are summarized in Fig. 2.

Proof Sketch: The achievability comes from the compression schemes³ proposed in Section V. The average-case converse for $\mathcal{X}(\mathcal{S}_n, d_{\mathbf{x}, \ell_1})$ can be shown via the geometry of permutation spaces in Appendix A. Then because a D -ball in $\mathcal{X}(\mathcal{S}_n, d_{\mathbf{x}, \ell_1})$ has the largest volume (cf. (7)), a converse for other permutation spaces can be inferred.

The rest of the proof follows from the simple fact that an achievability scheme for the worst-case distortion is also an achievability scheme for the average-case distortion, and a converse for the average-case distortion is also a converse for the worst-case distortion.

³Achievability results can also follow from simple random choice construction of covering codes, which are quite standard [27]. Instead we provide explicit constructions.

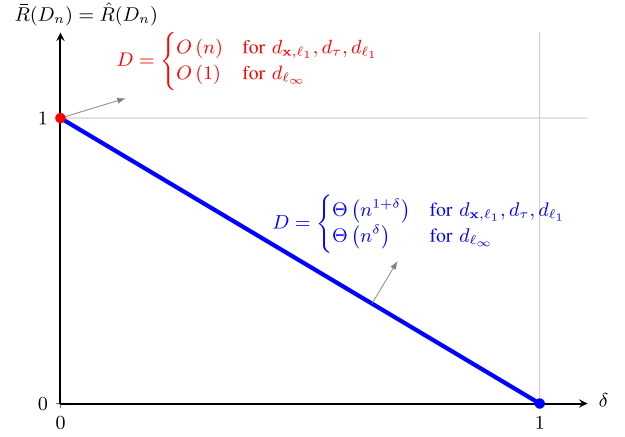


Fig. 2. Rate-distortion function for permutation spaces $\mathcal{X}(\mathcal{S}_n, d_{\mathbf{x}, \ell_1})$, $\mathcal{X}(\mathcal{S}_n, d_\tau)$, $\mathcal{X}(\mathcal{S}_n, d_{\ell_1})$, and $\mathcal{X}(\mathcal{S}_n, d_{\ell_\infty})$.

We present the detailed proof in Appendix B-B. ■

Because the rate-distortion functions under average-case and worst-case distortion coincide, if we require

$$\lim_{n \rightarrow \infty} \mathbb{P}[d(f_n(\sigma), \sigma) > D_n] = 0 \quad (15)$$

instead of $\mathbb{E}[d(f_n(\sigma), \sigma)] \leq D_n$ in Definition 6, then the asymptotic rate-distortion trade-off remains the same.

Given the number of elements n and a distortion level D , we can compute the number of bits needed by first computing δ via the asymptotic relationship $\log D / \log n - 1$ (for permutation spaces $\mathcal{X}(\mathcal{S}_n, d_{\mathbf{x}, \ell_1})$, $\mathcal{X}(\mathcal{S}_n, d_\tau)$, and $\mathcal{X}(\mathcal{S}_n, d_{\ell_1})$) or $\log D / \log n$ (for permutation space $\mathcal{X}(\mathcal{S}_n, d_{\ell_\infty})$), then obtain the number of bits needed via $(1 - \delta)n \log_2 n$.

B. Higher Order Term Analysis

As mentioned in Section II, for small- and large-distortion regimes it is of interest to understand the trade-off between rate and distortion via the higher order term defined in (6). In this section we present the analysis for both regimes in permutation spaces $\mathcal{X}(\mathcal{S}_n, d_\tau)$ and $\mathcal{X}(\mathcal{S}_n, d_{\mathbf{x}, \ell_1})$.

Theorem 5: In the permutation space $\mathcal{X}(\mathcal{S}_n, d_\tau)$, when $D_n = an^\delta$, $0 < \delta \leq 1$, for the worst-case distortion, $\underline{r}_\tau^s(D_n) \leq \overline{r}_\tau^s(D_n) \leq \overline{r}_\tau^s(D_n)$, where

$$\underline{r}_\tau^s(D_n) = \begin{cases} -a(1 - \delta)n^\delta \log n + O(n^\delta), & 0 < \delta < 1 \\ -n \left[\log \frac{(1+a)^{1+a}}{a^a} \right] + o(n), & \delta = 1, \end{cases} \quad (16)$$

$$\overline{r}_\tau^s(D_n) = \begin{cases} -n^\delta \frac{a \log 2}{2} + O(1), & 0 < a < 1 \\ -n^\delta \frac{\log [2a]!}{[2a]} + O(1), & a \geq 1. \end{cases} \quad (17)$$

When $D_n = bn^2$, $0 < b \leq 1/2$, $\underline{r}_\tau^1(D_n) \leq r(D_n) \leq \overline{r}_\tau^1(D_n)$, where

$$\underline{r}_\tau^1(D_n) = \max \left\{ 0, n \log 1 / (2be^2) \right\}, \quad (18)$$

$$\overline{r}_\tau^1(D_n) = n \log \lceil 1 / (2b) \rceil + O(\log n). \quad (19)$$

Remark 6: Some of the results above for $\mathcal{X}(\mathcal{S}_n, d_\tau)$, since their first appearances in the conference version [28],

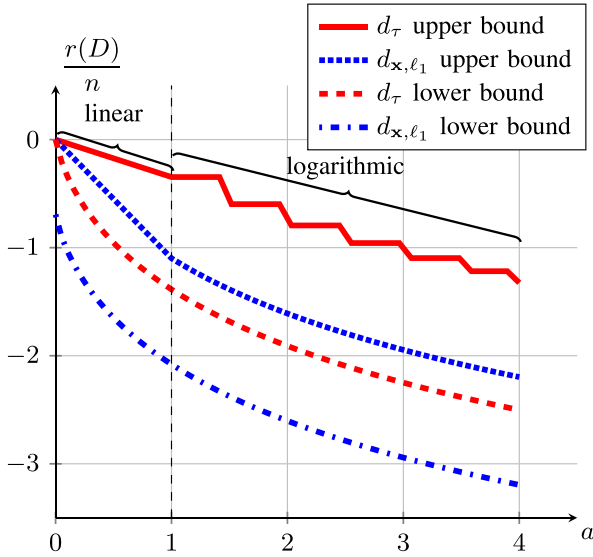


Fig. 3. Higher-order trade-off between rate and distortion in the small distortion regime with $D = an$. The slope discontinuities of the d_τ upper bound in the range of $a \geq 1$ is due to the flooring in (17).

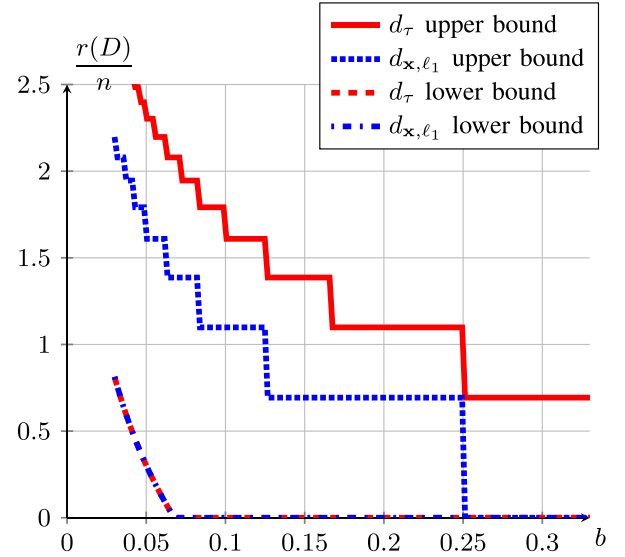


Fig. 4. Higher-order trade-off between rate and distortion in the large distortion regime with $D = bn^2$. The lower bounds for d_τ and d_{x, ℓ_1} are identical.

have been improved subsequently by [29]. More specifically, for the small distortion regime, [29, Lemmas 7 and 10] provides an improved upper bound and show that $r_\tau^s(D_n) = \overline{r_\tau^s(D_n)}$ in (16). For the large distortion regime, [29, Lemma 11] shows a lower bound that is tighter than (18).

Theorem 6: In the permutation space $\mathcal{X}(S_n, d_{x, \ell_1})$, when $D_n = an^\delta$, $0 < \delta \leq 1$,

$$\underline{r_{x, \ell_1}^s(D_n)} \leq r(D_n) \leq \overline{r_{x, \ell_1}^s(D_n)},$$

where $\underline{r_{x, \ell_1}^s(D_n)} = \underline{r_\tau^s(D_n)} - n^\delta \log 2$ (cf. (16)) and

$$\overline{r_{x, \ell_1}^s(D_n)} = \begin{cases} -\lfloor n^\delta \rfloor \log(2a - 1) & a > 1 \\ -\lceil an^\delta \rceil \log 3 & 0 < a \leq 1. \end{cases}$$

When $D_n = bn^2$, $0 < b \leq 1/2$,

$$\underline{r_{x, \ell_1}^1(D_n)} \leq r(D_n) \leq \overline{r_{x, \ell_1}^1(D_n)},$$

where $\underline{r_{x, \ell_1}^1(D_n)} = \underline{r_\tau^1(D_n)}$ (cf. (18)) and $\overline{r_{x, \ell_1}^1(D_n)} = n \log \lceil 1/(4b) \rceil + O(1)$.

Proof for Theorem 5 and Theorem 6: The achievability is presented in Section V-D and Section V-E. For converse, note that for a distortion measure d ,

$$|\mathcal{C}_n| N_d(D_n) \geq n!,$$

where $N_d(D_n)$ is the maximum size of balls with radius D_n in the corresponding permutation space $\mathcal{X}(S_n, d)$ (cf. Appendix A for definitions), then a lower bound on $|\mathcal{C}_n|$ follows from the upper bound on $N_d(D_n)$ in Lemma 15 and Lemma 17. We omit the details as it is analogous to the proof of Theorem 4. ■

The bounds to $r(D_n)$ of both Kendall tau distance and inversion- ℓ_1 distance in both small and large distortion regimes are shown in Fig. 3 and Fig. 4.

V. COMPRESSION SCHEMES

Though the permutation space has a complicated structure, in this section we show two rather straightforward compression schemes, *sorting subsequences* and *component-wise scalar quantization*, which are optimal as they achieve the rate-distortion functions in Theorem 4. We first describe these two key compression schemes in Section V-A and Section V-B respectively. Then in Sections V-C to V-E, we show that by simply applying these schemes with proper parameters, we can achieve the corresponding trade-offs between rate and distortion shown in Section IV.

The equivalence relationships in Theorem 3 suggest these two compression schemes achieve the same asymptotic performance. In addition, it is not hard to see that in general sorting subsequences has higher time complexity (e.g., $O(n \log n)$ for moderate distortion regime) than the time complexity of component-wise scalar quantization (e.g., $O(n)$ for moderate distortion regime). However, these two compression schemes operate on the permutation domain and the inversion vector of permutation domain respectively, and the time complexity to convert a permutation from its vector representation to its inversion vector representation is $\Theta(n \log n)$ [24, Sec. 5.1.1, Exercise 6]. Therefore, the cost of transforming a permutation between different representations should be taken into account when selecting the compression scheme.

A. Quantization by Sorting Subsequences

In this section we describe the basic building block for lossy source coding in permutation space $\mathcal{X}(S_n, d_{\ell_1})$, $\mathcal{X}(S_n, d_{\ell_\infty})$ and $\mathcal{X}(S_n, d_\tau)$: sorting subsequences, either of the given permutation σ or of its inverse σ^{-1} . This operation reduces the number of possible permutations and thus the code rate, but introduces distortion. By choosing the proper number

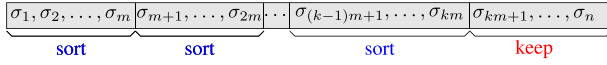


Fig. 5. Quantization by sorting subsequences.

of subsequences with proper lengths, we can achieve the corresponding rate-distortion function.

More specifically, we consider a code obtained by the sorting the first k subsequences with length m , $2 \leq m \leq n$, $km \leq n$:

$$\mathcal{C}(k, m, n) \triangleq \{f_{k,m}(\sigma) : \sigma \in \mathcal{S}_n\}$$

where $\sigma' = f_{k,m}(\sigma)$ satisfies

$$\begin{aligned} \sigma'[im + 1 : (i + 1)m] &= \text{sort}(\sigma[im + 1 : (i + 1)m]), \\ &0 \leq i \leq k, \\ \sigma'(j) &= \sigma(j), \quad j > km. \end{aligned}$$

This procedure is illustrated in Fig. 5.

Then $|\mathcal{C}(k, m, n)| = n!/(m^k)$, and we define the (log) size reduction as

$$\begin{aligned} \Delta(k, m) &\triangleq \log \frac{n!}{|\mathcal{C}(k, m, n)|} = k \log m! \\ &\stackrel{(a)}{=} k \left[m \log(m/e) + \frac{1}{2} \log m + \left(\frac{1}{m}\right) \right], \end{aligned}$$

where (a) follows from Stirling's approximation in (1). Therefore,

$$\Delta(k, m) = \begin{cases} km \log m + o(km \log m) & m = \Omega(1) \\ k \log m! & m = \Theta(1). \end{cases}$$

We first calculate the worst-case and average-case distortions for permutation space $\mathcal{X}(\mathcal{S}_n, d_\tau)$:

$$\hat{D}_{d_\tau}(k, m) = k \frac{m(m-1)}{2} \leq km^2/2 \quad (20)$$

$$\bar{D}_{d_\tau}(k, m) = k \frac{m(m-1)}{4} \leq km^2/4 \quad (21)$$

where (20) is from (38).

Remark 7: Due to the close relationship between the Kendall tau distance and the Spearman's footrule shown in (11), the following codebook via the inverse permutations $\{\sigma^{-1}\}$ is an equivalent construction to the codebook for Kendall tau distance above.

1) Construct a vector $a(\sigma)$ such that for $1 \leq i \leq k$,

$$a(i) = j \text{ if } \sigma^{-1}(i) \in [(j-1)m + 1, jm], \quad 1 \leq j \leq k.$$

Then a contains exactly m values of integers j .

2) Form a permutation π' by replacing the length- m subsequence of a that corresponds to value j by vector $[(j-1)m + 1, (j-1)m + 2, \dots, jm]$.

It is not hard to see that the set of $\{\pi'^{-1}\}$ forms a codebook with the same size with distortion in Kendall tau distance upper bounded by $km^2/2$.

Similarly, for permutation space $\mathcal{X}(\mathcal{S}_n, d_{\ell_1})$ and $\mathcal{X}(\mathcal{S}_n, d_{\ell_\infty})$, we consider sorting subsequences in the inverse permutation domain, where

$$\mathcal{C}'(k, m, n) \triangleq \{\pi^{-1} : \pi = f_{k,m}(\sigma^{-1}), \sigma \in \mathcal{S}_n\}.$$

It is straightforward that $\mathcal{C}'(k, m, n)$ has the same cardinality as $\mathcal{C}(k, m, n)$ and hence code rate reduction $\Delta(k, m)$. And the worst-case and average-case distortions satisfy

$$\hat{D}_{\ell_\infty}(k, m) = m - 1 \quad (22)$$

$$\bar{D}_{\ell_\infty}(k, m) \leq m - 1 \quad (23)$$

$$\hat{D}_{\ell_1}(k, m) = k \left\lfloor \frac{m^2}{2} \right\rfloor / 2 \leq km^2/2 \quad (24)$$

$$\bar{D}_{\ell_1}(k, m) = k(m^2 - 1)/3, \quad (25)$$

where (24) comes from Table I and (25) comes from (37).

B. Component-Wise Scalar Quantization

To compress in the space of $\mathcal{X}(\mathcal{S}_n, d_{\mathbf{x}, \ell_1})$, component-wise scalar quantization suffices, due to the product structure of the inversion vector space \mathcal{G}_n .

More specifically, to quantize the k points in $[0 : k - 1]$, where $k = 2, \dots, n$, with m uniformly spaced points, the maximal distortion is

$$\hat{D}_{\mathbf{x}, \ell_1}(k, m) = \lceil (k/m - 1)/2 \rceil, \quad (26)$$

Conversely, to achieve distortion $\hat{D}_{\mathbf{x}, \ell_1}$ on $[0 : k - 1]$, we need

$$m = \left\lceil \frac{k}{2\hat{D}_{\mathbf{x}, \ell_1} + 1} \right\rceil \quad (27)$$

points.

C. Compression in the Moderate Distortion Regime

In this section we provide compression schemes in the moderate distortion regime, where for any $0 < \delta < 1$, $D_n = \Theta(n^\delta)$ for $\mathcal{X}(\mathcal{S}_n, d_{\ell_\infty})$ and $D_n = \Theta(n^{1+\delta})$ for $\mathcal{X}(\mathcal{S}_n, d_{\ell_1})$, $\mathcal{X}(\mathcal{S}_n, d_\tau)$ and $\mathcal{X}(\mathcal{S}_n, d_{\mathbf{x}, \ell_1})$. While Theorem 3 indicates a source code for $\mathcal{X}(\mathcal{S}_n, d_{\ell_\infty})$ can be transformed into source codes for other spaces under both average-case and worst-case distortions, we develop explicit compression schemes for each permutation spaces as the transformation of permutation representations incur additional computational complexity and hence may not be desirable.

1) *Permutation Space $\mathcal{X}(\mathcal{S}_n, d_{\ell_\infty})$* : Given distortion $D_n = \Theta(n^\delta)$, we apply the sorting subsequences scheme in Section V-A and choose $m = D_n + 1$, which ensures the maximal distortion is no more than D_n , and $k = \lfloor n/m \rfloor$, which indicates

$$km = \lfloor n/m \rfloor m = n + O(n^\delta)$$

$$\log m = \delta \log n + o(1)$$

$$\begin{aligned} \Delta(k, m) &= km \log m + o(km \log m) \\ &= \delta n \log n + O(n). \end{aligned}$$

2) *Permutation Spaces $\mathcal{X}(\mathcal{S}_n, d_{\ell_1})$ and $\mathcal{X}(\mathcal{S}_n, d_\tau)$* : Given distortion $D_n = \Theta(n^{1+\delta})$, we apply the sorting subsequences scheme in Section V-A and choose

$$m = (1/\alpha) \lfloor D_n/n \rfloor \leq D_n/(n\alpha)$$

$$k = \lfloor n/m \rfloor,$$

TABLE II
VALUES OF α FOR DIFFERENT COMPRESSION SCENARIOS

α	average-case	worst-case
$\mathcal{X}(\mathcal{S}_n, d_{\ell_1})$	1/3	1/2
$\mathcal{X}(\mathcal{S}_n, d_\tau)$	1/4	1/2

then

$$\begin{aligned} km &= n - |O(n^\delta)| \\ D &\leq \alpha km^2 \leq D_n \\ \Delta(k, m) &= \delta n \log n - n \log(ae) + o(n), \end{aligned}$$

where the constant α depends on the distortion measure and whether we are considering worst-case or average-case distortion, as shown in (20), (21), (24) and (25), and is summarized in Table II.

3) *Permutation Space $\mathcal{X}(\mathcal{S}_n, d_{x, \ell_1})$* : Given distortion $D_n = \Theta(n^{1+\delta})$, we apply the component-wise scalar quantization scheme in Section V-B and choose the quantization error of the coordinate with range $[0 : k-1]$ $D^{(k)}$ to be

$$D^{(k)} = \frac{kD}{(n+1)^2},$$

then

$$\begin{aligned} m_k &= \left\lceil k / \left(2 + D^{(k)} + 1 \right) \right\rceil = \left\lceil \frac{k(n+1)^2}{2kD_n + (n+1)^2} \right\rceil \\ &\leq \left\lceil \frac{(n+1)^2}{2D_n} \right\rceil, \end{aligned}$$

and the overall distortion and the codebook size satisfy

$$\begin{aligned} D &= \sum_{k=2}^n \frac{(n-1)(n+2)}{(n+1)^2} D_n \leq D_n, \\ \log |C_n| &= \sum_{k=2}^n \log m_k \leq n \log \left\lceil \frac{(n+2)^2}{2D_n} \right\rceil \\ &= (1-\delta)n \log n + O(n). \end{aligned}$$

D. Compression in the Small Distortion Regime

In this section we provide compression schemes in the small distortion regime for $\mathcal{X}(\mathcal{S}_n, d_\tau)$ and $\mathcal{X}(\mathcal{S}_n, d_{x, \ell_1})$, where for any $a > 0, 0 < \delta < 1, D_n = an^\delta$.

1) *Permutation Space $\mathcal{X}(\mathcal{S}_n, d_\tau)$* : When $a \geq 1$, let $m = \lfloor 2a \rfloor$ and $k = \lfloor n^\delta/m \rfloor$, then

$$\begin{aligned} \Delta(k, m) &= k \log m! \\ &\geq (n^\delta/m - 1) \log m! = \frac{\log \lfloor 2a \rfloor!}{\lfloor 2a \rfloor} n^\delta + O(1). \end{aligned}$$

And the worst-case distortion is upper bounded by

$$km^2/2 \leq \frac{n^\delta m}{2} \leq an^\delta = D_n.$$

When $0 < a < 1$, let $m = 2$ and $k = \lfloor D_n/2 \rfloor$, then

$$\Delta(k, m) = k \log m! = \left\lfloor \frac{D_n}{2} \right\rfloor \log 2 = \frac{a \log 2}{2} n^\delta + O(1).$$

And the worst-case distortion is no more than $km^2/2 \leq D_n$.

2) *Permutation Space $\mathcal{X}(\mathcal{S}_n, d_{x, \ell_1})$* : When $a > 1$, let

$$m_k = \begin{cases} k & k \leq n - \lfloor n^\delta \rfloor \\ \lceil k/(2a-1) \rceil & k > n - \lfloor n^\delta \rfloor \end{cases}, \quad k = 2, \dots, n$$

then the distortion $D^{(k)}$ for each coordinate k satisfies

$$D^{(k)} \leq \begin{cases} a & k \leq \lfloor n^\delta \rfloor \\ 0 & k > \lfloor n^\delta \rfloor \end{cases}, \quad k = 2, 3, \dots, n,$$

and hence overall distortion is $\sum_{k=2}^n D^{(k)} = (\lfloor n^\delta \rfloor)a \leq D_n$. In addition, the codebook size

$$\left| \hat{C}_n \right| = \prod_{k=2}^n m_k \leq (1/(2a-1))^{\lfloor n^\delta \rfloor} \prod_{k=2}^n k.$$

Therefore, $\log \left| \hat{C}_n \right| \leq \log n! - \lfloor n^\delta \rfloor \log(2a-1) + O(\log n)$.

When $a \leq 1$, let

$$m_k = \begin{cases} \lceil k/3 \rceil & k < \lceil D_n \rceil \\ k & k \geq \lceil D_n \rceil \end{cases}, \quad k = 2, \dots, n$$

and apply uniform quantization on the coordinate k of the inversion vector with m_k points, Then the distortion $D^{(k)}$ for each coordinate k satisfies

$$D^{(k)} \leq \begin{cases} 1 & k < \lceil D_n \rceil \\ 0 & k \geq \lceil D_n \rceil \end{cases}, \quad k = 2, 3, \dots, n,$$

and hence overall distortion is $\sum_{k=2}^n D^{(k)} = \lceil D_n \rceil - 1 \leq D_n$. In addition, the codebook size

$$\begin{aligned} \left| \hat{C}_n \right| &= \prod_{k=2}^n m_k \leq \prod_{k=2}^{\lceil D_n \rceil - 1} (k+3)/3 \prod_{k=\lceil D_n \rceil}^n k \\ &= \frac{1}{3^{\lceil D_n \rceil - 1}} \lceil D_n \rceil (\lceil D_n \rceil + 1) (\lceil D_n \rceil + 2) \prod_{k=5}^{n-1} k. \end{aligned}$$

Therefore, $\log \left| \hat{C}_n \right| \leq \log n! - \lceil an^\delta \rceil \log 3 + O(\log n)$.

E. Compression in the Large Distortion Regime

In this section we provide compression schemes in the large distortion regime for $\mathcal{X}(\mathcal{S}_n, d_\tau)$ and $\mathcal{X}(\mathcal{S}_n, d_{x, \ell_1})$, where for any $0 < b < 1/2, D_n = bn^2$.

1) *Permutation Space $\mathcal{X}(\mathcal{S}_n, d_\tau)$* : Let $k = \lceil 1/(2b) \rceil$ and $m = \lfloor n/k \rfloor$, then

$$\begin{aligned} \Delta(k, m) &= k \log m! \geq k \log(n/k - 1)! \\ &\geq k[n/k \log(n/k) - n/k \log e + O(\log n)] \\ &= n \log(n/e) - n \log \lceil 1/(2b) \rceil + O(\log n). \end{aligned}$$

Hence $\hat{r}(D_n) = \log n! - \Delta(k, m) \leq \log \lceil 1/(2b) \rceil + O(\log n)$. And the worst-case distortion is upper bounded by

$$km^2/2 \leq n^2/(2k) \leq n^2/(1/b) = bn^2.$$

2) *Permutation Space* $\mathcal{X}(\mathcal{S}_n, d_{\mathbf{x}, \ell_1})$: Let $m_k = \lceil k/(4b(k-1) + 1) \rceil$, $k = 2, \dots, n$. The distortion $D^{(k)}$ for each coordinate k satisfies

$$D^{(k)} = \left\lceil \frac{1}{2} \left(\frac{k}{m} - 1 \right) \right\rceil \leq \lceil 2b(k-1) \rceil, \quad k = 2, 3, \dots, n,$$

and hence overall distortion $\sum_{k=2}^n D^{(k)} \leq \sum_{k=2}^n 2b(k-1) + 1 \leq (b+1/n)n(n-1)$. In addition, the codebook size

$$|\hat{\mathcal{C}}_n| = \prod_{k=2}^n m_k \leq \prod_{k=2}^n \left\lceil \frac{k-1}{4b(k-1)} \right\rceil \leq \left\lceil \frac{1}{4b} \right\rceil^{n-1}.$$

Therefore, $\log |\hat{\mathcal{C}}_n| \leq n \log \lceil 1/(4b) \rceil + O(1)$.

VI. COMPRESSION OF PERMUTATION SPACE WITH MALLOW'S MODEL

In this section we depart from the uniform distribution assumption and investigate the compression of a permutation space with a non-uniform model—Mallows model [18], a model with a wide range of applications such as ranking, partial ranking, and even algorithm analysis (see [30, Sec. 2e] and the references therein). In the context of storing user ranking data, the Mallows model (or more generally, the mixture of Mallows model) captures the phenomenon that user rankings are often similar to each other. In the application of approximate sorting, the Mallows model may be used to model our prior knowledge that permutations that are similar to the reference permutation are more likely.

Definition 9 (Mallows Model): We denote a Mallows model with reference permutation (mode) π and parameter q as $\mathcal{M}(\pi, q)$, where for each permutation $\sigma \in \mathcal{S}_n$,

$$\mathbb{P}[\sigma; \mathcal{M}(\pi, q)] = \frac{q^{d_\tau(\sigma, \pi)}}{Z_{q, \pi}},$$

where normalization $Z_{q, \pi} = \sum_{\sigma \in \mathcal{S}_n} p^{d_\tau(\sigma, \pi)}$. In particular, when the mode $\pi = \text{Id}$, $Z_q \triangleq Z_{q, \text{Id}} = [n]_q!$ [30, (2.9)], where $[n]_q!$ is the q -factorial $[n]_q! = [n]_q [n-1]_q \dots [1]_q$ and $[n]_q$ is the q -number

$$[n]_q \triangleq \begin{cases} \frac{1-q^n}{1-q} & q \neq 1 \\ n & q = 1 \end{cases}.$$

As we shall see, the entropy of the permutation space with a Mallows model is in general $\Theta(n)$, implying lower storage space requirement and *potentially* lower query complexity for sorting. Since the Mallows model is specified via the Kendall tau distance, we use Kendall tau distance as the distortion measure, and focus our attention on the average-case distortion.

Noting the Kendall tau distance is right-invariant [22], for the purpose of compression, we can assume the mode $\pi = \text{Id}$ without loss of generality, and denote the Mallows model by $\mathcal{M}(q) \triangleq \mathcal{M}(\text{Id}, q)$.

A. Repeated Insertion Model

The Mallows model can be generated through a process named *repeated insertion model* (RIM), which is introduced in [31] and later applied in [21].

Definition 10 (Repeated Insertion Model): Given a reference permutation $\pi \in \mathcal{S}_n$ and a set of insertion probabilities $\{p_{i,j}, 1 \leq i \leq n, 1 \leq j \leq i\}$, RIM generates a new output σ by repeated inserting $\pi(i)$ before the j -th element in σ with probability $p_{i,j}$ (when $j = i$, we append $\pi(i)$ at the end of σ).

Remark 8: Note that the insertion probabilities at step i is independent of the realizations of earlier insertions.

The i -th step in the RIM process involves sampling from a multinomial distribution with parameter $p_{i,j}, 1 \leq j \leq i$. If we denote the sampling outcome at the i -th step of the RIM process by $a_i, 1 \leq i \leq n$, then a_i indicates the location of insertion. By Definition 10, a vector $\mathbf{a} = [a_1, a_2, \dots, a_n]$ has an one-one correspondence to a permutation, and we called this vector \mathbf{a} an *insertion vector*.

Lemma 7: Given a RIM with reference permutation $\pi = \text{Id}$ and insertion vector \mathbf{a}_σ , then the corresponding permutation σ satisfies

$$\mathbf{a}_\sigma(i) = i - \tilde{\mathbf{x}}_\sigma(i),$$

where $\tilde{\mathbf{x}}_\sigma$ is an extended inversion vector, which simply is an inversion vector \mathbf{x}_σ with 0 prepended.

$$\tilde{\mathbf{x}}_\sigma(i) = \begin{cases} 0 & i = 1 \\ \mathbf{x}_\sigma(i-1) & 2 \leq i \leq n \end{cases}$$

Therefore,

$$\begin{aligned} d_\tau(\sigma, \text{Id}) &= d_{\mathbf{x}, \ell_1}(\sigma, \text{Id}) \\ &= \sum_{i=1}^n (i - \mathbf{a}_\sigma(i)) = \binom{n+1}{2} - \sum_{i=1}^n \mathbf{a}_\sigma(i). \end{aligned}$$

Example 5: For $n = 4$ and reference permutation $\text{Id} = [1, 2, 3, 4]$, if $\mathbf{a} = [1, 1, 1, 1]$, then $\sigma = [4, 3, 2, 1]$, which corresponds to $\tilde{\mathbf{x}}_\sigma = [0, 1, 2, 3]$.

Theorem 8 (Mallows Model via RIM [21], [31]): Given reference permutation π and

$$p_{i,j} = \frac{q^{i-j}}{1+q+\dots+q^{i-1}}, \quad 1 \leq j \leq i \leq n,$$

RIM induces the same distribution as the Mallows model $\mathcal{M}(\pi, q)$.

This observation allows us to convert compressing the Mallows model to a standard problem in source coding.

Theorem 9: Compressing a Mallows model is equivalent to compressing a vector source $\mathbf{X} = [X_1, X_2, \dots, X_n]$, where X_i is a geometric random variable truncated at $i-1$, $1 \leq i \leq n$, i.e.,

$$\begin{aligned} \mathbb{P}[X_i = j] &= \frac{q^j}{\sum_{j'=0}^{i-1} q^{j'}} \\ &= \frac{q^j(1-q)}{1-q^i}, \quad 0 \leq j \leq i-1 \end{aligned}$$

Proof: This follows directly from Lemma 7 and Theorem 8. \blacksquare

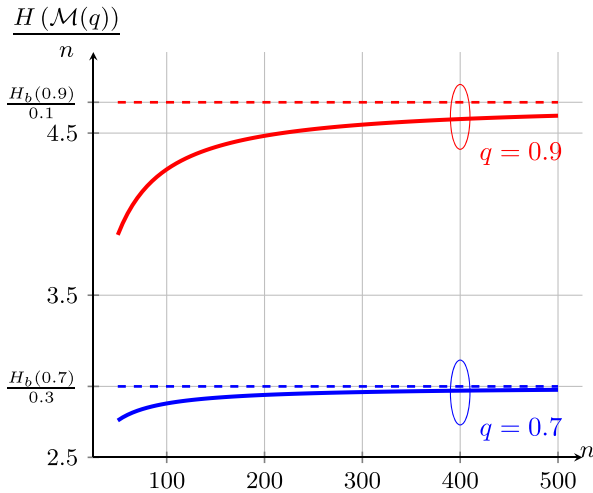


Fig. 6. Entropy of the Mallows model for $q = 0.7$ and $q = 0.9$, where the dashed lines are the coefficients of the linear terms, $H_b(q)/(1 - q)$.

B. Lossless Compression

We consider the lossless compression of Mallows model.

Corollary 10:

$$H(\mathcal{M}(q)) = H(\mathcal{M}(1/q))$$

Proof: This follows directly from Theorem 8. ■

Lemma 11 (Entropy of Mallows Model):

$$H(\mathcal{M}(q)) = \sum_{k=1}^n H(X_k) = \begin{cases} \frac{H_b(q)}{1-q}n + g(n, q) & q \neq 1 \\ \log n! & q = 1, \end{cases}$$

where $\{X_k\}$ are truncated geometric random variables defined in Theorem 9, $H_b(\cdot)$ is the binary entropy function, $g(n, q) = \Theta(1)$, and $\lim_{q \rightarrow 0} g(n, q) = 0$.

The proof is presented in Appendix C-A. Fig. 6 shows plots of $H(\mathcal{M}(q))$ for different values of n and q .

Remark 9: Performing entropy-coding for each X_i , $1 \leq i \leq n$ is sub-optimal in general as the overhead is $O(1)$ for each i and hence $O(n)$ for \mathbf{X} , which is on the same order of the entropy $H(\mathcal{M}(q))$ when $q \neq 1$.

C. Lossy Compression

By Theorem 9, the lossy compression of Mallows model is equivalent to the lossy compression of the independent non-identical source \mathbf{X} . However, it is unclear whether an analytical solution of the rate-distortion function for this source can be derived, and below we try to gain some insights via characterizing the typical set of the Mallows model in Lemma 12, which implies that at rate 0, the average-case distortion is $\Theta(n)$, while under the uniform distribution, Theorem 4 indicates that it takes $n \log n + o(n \log n)$ bits to achieve average-case distortion of $\Theta(n)$.

Lemma 12 (Typical Set of Mallows Model): There exists $c_0(q)$, a constant that depends on q only, such that for any $r_0 \geq c_0(q)n$,

$$\lim_{n \rightarrow \infty} \mathbb{P}[d_\tau(\text{Id}, \sigma) \leq r_0; \mathcal{M}(\text{Id}, q)] = 1.$$

The proof is presented in Appendix C-B.

Remark 10: As pointed out in [31], Mallows model is only one specific distributional model that is induced by RIM. It is possible to generalize our analysis above to other distributional models that are also induced by RIM.

VII. CONCLUDING REMARKS

In this paper, we first investigate the lossy compression of permutations under both worst-case distortion and average-case distortions with uniform source distribution. We consider Kendall tau distance, Spearman’s footrule, Chebyshev distance and inversion- ℓ_1 distance as distortion measures. Regarding the lossy storage of ranking, our results provide the fundamental trade-off between storage and accuracy. Regarding approximate sorting, our results indicate that, given a moderate distortion D_n (see Section II for definition), an approximate sorting algorithm must perform *at least* $\Theta(n \log n)$ pairwise comparisons, where constant implicitly in the Θ term is exactly the rate-distortion function $R(D_n)$. As mentioned, this performance is indeed achieved by the multiple selection algorithm in [12]. This shows our information-theoretic lower bound for approximate sorting is tight.

In practical ranking systems where prior knowledge on the ranking is available, non-uniform model may be more appropriate. Our results on the Mallows model show that the entropy could be much lower ($\Theta(n)$) than the uniform model ($\Theta(n \log n)$). This greater compression ratio suggests that it would be worthwhile to solve the challenge of designing entropy-achieving compression schemes with low computational complexity for Mallows model. A deeper understanding on the rate-distortion trade-off of non-uniform models would be beneficial to the many areas that involves permutation model with a non-uniform distribution, such as the problem of learning to rank [21] and algorithm analysis [30].

APPENDIX A

GEOMETRY OF PERMUTATION SPACES

In this section we provide results on the geometry of the permutation space that are useful in deriving rate-distortion bounds.

We first define D -balls centered at $\sigma \in \mathcal{S}_n$ with radius D under distance $d(\cdot, \cdot)$ and their maximum sizes:

$$B_d(\sigma, D) \triangleq \{\pi : d(\pi, \sigma) \leq D\}, \tag{28}$$

$$N_d(D) \triangleq \max_{\sigma \in \mathcal{S}_n} |B_d(\sigma, D)|. \tag{29}$$

Let $B_\tau(\sigma, D)$, $B_{\ell_1}(\sigma, D)$ and $B_{\mathbf{x}, \ell_1}(\sigma, D)$ be the balls that correspond to the Kendall tau distance, ℓ_1 distance of the permutations, and ℓ_1 distance of the inversion vectors, and $N_\tau(D)$, $N_{\ell_1}(D)$, and $N_{\mathbf{x}, \ell_1}(D)$ be their maximum sizes respectively.

Note that (12) implies $B_\tau(\sigma, D) \subset B_{\mathbf{x}, \ell_1}(\sigma, D)$ and thus $N_\tau(D) \leq N_{\mathbf{x}, \ell_1}(D)$. Below we establish upper bounds for $N_{\mathbf{x}, \ell_1}(D)$ and $N_\tau(D)$, which are useful for establishing converse results later.

Lemma 13: For $0 \leq D \leq n$,

$$N_\tau(D) \leq \binom{n + D - 1}{D}. \tag{30}$$

Proof: Let the number of permutations in \mathcal{S}_n with at most k inversions be $T_n(d) \triangleq \sum_{k=0}^d K_n(k)$, where $K_n(k)$ is defined in (2). Since $\mathcal{X}(\mathcal{S}_n, d_\tau)$ is a regular metric space,

$$N_\tau(D) = T_n(D),$$

which is noted in several references such as [24]. An expression for $K_n(D)$ (and thus $T_n(D)$) for $D \leq n$ appears in [24] (see [4] also). The following bound is weaker but sufficient in our context.

By induction, or [32], $T_n(D) = K_{n+1}(D)$ when $D \leq n$. Then noting that for $k < n$, $K_n(k) = K_n(k-1) + K_{n-1}(k)$ [24, Sec. 5.1.1] and for any $n \geq 2$,

$$K_n(0) = 1, \quad K_n(1) = n-1, \quad K_n(2) = \binom{n}{2} - 1,$$

by induction, we can show that when $1 \leq k < n$,

$$K_n(k) \leq \binom{n+k-2}{k}. \quad (31)$$

The product structure of $\mathcal{X}(\mathcal{S}_n, d_{\mathbf{x}, \ell_1})$ leads to a simpler analysis of the upper bound of $N_{\mathbf{x}, \ell_1}(D)$.

Lemma 14: For $0 \leq D \leq n(n-1)/2$,

$$N_{\mathbf{x}, \ell_1}(D) \leq 2^{\min\{n, D\}} \binom{n+D}{D}. \quad (32)$$

Proof: For any $\sigma \in \mathcal{S}_n$, let $\mathbf{x} = \mathbf{x}_\sigma \in \mathcal{G}_n$, then

$$|B_{\mathbf{x}, \ell_1}(D)| = \sum_{r=0}^D |\{\mathbf{y} \in \mathcal{G}_n : d_{\ell_1}(\mathbf{x}, \mathbf{y}) = r\}|.$$

Let $\mathbf{d} \triangleq |\mathbf{x} - \mathbf{y}|$, and $Q(n, r)$ be the number of integer solutions of the equation $z_1 + z_2 + \dots + z_n = r$ with $z_i \geq 0, 0 \leq i \leq n$, then it is well known [33, Sec. 1.2] that

$$Q(n, r) = \binom{n+r-1}{r},$$

and it is not hard to see that the number of such $\mathbf{d} = [d_1, d_2, \dots, d_{n-1}]$ that satisfies $\sum_{i=1}^{n-1} d_i = r$ is upper bounded by $Q(n-1, r)$. Given \mathbf{x} and \mathbf{d} , at most $m \triangleq \min\{D, n\}$ elements in $\{y_i, 0 \leq i \leq n\}$ correspond to $y_i = x_i \pm d_i$. Therefore, for any \mathbf{x} , $|\{\mathbf{y} \in \mathcal{G}_n : d_{\ell_1}(\mathbf{x}, \mathbf{y}) = r\}| \leq 2^m Q(n, r)$ and hence

$$|B_{\ell_1}(\mathbf{x}, D)| \leq \sum_{r=0}^D 2^m Q(n, r) = 2^m \binom{n+D}{D}.$$

Below we upper bound $\log N_\tau(D)$ and $\log N_{\mathbf{x}, \ell_1}(D)$ for small, moderate and large D regimes in Lemmas 15 to 17 respectively.

Lemma 15 (Small Distortion Regime): When $D = an^\delta$, $0 < \delta \leq 1$ and $a > 0$ is a constant,

$$\log N_\tau(D) \leq \begin{cases} a(1-\delta)n^\delta \log n + O(n^\delta), & 0 < \delta < 1 \\ n \left[\log \frac{(1+a)^{1+a}}{a^a} \right] + o(n), & \delta = 1, \end{cases} \quad (33)$$

$$\log N_{\mathbf{x}, \ell_1}(D) \leq \begin{cases} a(1-\delta)n^\delta \log n + O(n^\delta), & 0 < \delta < 1 \\ n \left[2 + \log \frac{(1+a)^{1+a}}{a^a} \right] + o(n), & \delta = 1. \end{cases} \quad (34)$$

Proof: To upper bound $N_\tau(D)$, when $0 < \delta < 1$, we apply Stirling's approximation to (30) to have

$$\begin{aligned} & \log \binom{n+D-1}{D} \\ &= n \log \frac{n-1+D}{n-1} + D \log \frac{n-1+D}{D} + O(\log n). \end{aligned}$$

Substituting $D = an^\delta$, we obtain (33). When $\delta = 1$, the result follows from (9) in [34, Sec. 4]. The upper bound on $N_{\mathbf{x}, \ell_1}(D)$ can be obtained similarly via (32). ■

Lemma 16 (Moderate Distortion Regime): Given $D = \Theta(n^{1+\delta})$, $0 < \delta \leq 1$, then

$$\log N_\tau(D) \leq \log N_{\mathbf{x}, \ell_1}(D) \leq \delta n \log n + O(n). \quad (35)$$

Proof: Apply Stirling's approximation to (32) and substitute $D = \Theta(n^{1+\delta})$. ■

Remark 11: It is possible to obtain tighter lower and upper bounds for $\log N_\tau(D)$ and $\log N_{\mathbf{x}, \ell_1}(D)$ based on results in [4].

Lemma 17 (Large Distortion Regime): Given $D = bn(n-1) \in \mathbb{Z}^+$, then

$$\log N_\tau(D) \leq \log N_{\mathbf{x}, \ell_1}(D) \leq n \log(2ben) + O(\log n). \quad (36)$$

Proof: Substitute $D = bn(n-1)$ into (32). ■

A. Proof of (10)

Lemma 18: For any $\pi \in \mathcal{S}_n$, let σ be a permutation chosen uniformly from \mathcal{S}_n , and $X_{\ell_1} \triangleq d_{\ell_1}(\pi, \sigma)$, then

$$\mathbb{E}[X_{\ell_1}] = \frac{n^2-1}{3} \quad \text{Var}[X_{\ell_1}] = \frac{2n^3}{45} + O(n^2). \quad (37)$$

Proof:

$$\begin{aligned} \mathbb{E}[X_{\ell_1}] &= \frac{1}{n} \sum_{i=1}^n \sum_{j=1}^n |i-j| = \frac{2}{n} \sum_{i=1}^n \sum_{j=1}^i |i-j| \\ &= \frac{2}{n} \sum_{i=1}^n \sum_{j'=0}^{i-1} j' = \frac{1}{n} \sum_{i=1}^n (i^2 - i) \\ &= \frac{1}{n} \left(\sum_{i=1}^n i^2 - \sum_{i=1}^n i \right) \\ &= \frac{1}{n} \left(\frac{2n^3 + 3n^2 + n}{6} - \frac{n^2 + n}{2} \right) \\ &= \frac{n^2-1}{3}. \end{aligned}$$

And $\text{Var}[X_{\ell_1}]$ can be derived similarly [8, Table 1]. ■

Proof for (10): For any $c > 0$, $cn \cdot d_{\ell_\infty}(\pi, \sigma) \leq cn(n-1)$, and for any $c_1 < 1/3$, Lemma 18 and Chebyshev inequality indicate $\mathbb{P}[d_{\ell_1}(\pi, \sigma) < c_1 n(n-1)] = O(1/n)$. Therefore,

$$\begin{aligned} & \mathbb{P}[d_{\ell_1}(\pi, \sigma) \geq c_1 n \cdot d_{\ell_\infty}(\pi, \sigma)] \\ & \geq \mathbb{P}[d_{\ell_1}(\pi, \sigma) \geq c_1 n(n-1)] \\ & = 1 - \mathbb{P}[d_{\ell_1}(\pi, \sigma) < c_1 n(n-1)] \\ & = 1 - O(1/n). \end{aligned}$$

■

B. Proof of Theorem 2

Lemma 19: For any two permutations π, σ in \mathcal{S}_n such that $d_{\mathbf{x}, \ell_1}(\pi, \sigma) = 1$, $d_\tau(\pi, \sigma) \leq n - 1$.

Proof: Let $\mathbf{x}_\pi = [a_2, a_3, \dots, a_n]$ and $\mathbf{x}_\sigma = [b_2, b_3, \dots, b_n]$, then without loss of generality, we have for a certain $2 \leq k \leq n$,

$$a_i = \begin{cases} b_i & i \neq k \\ b_i + 1 & i = k. \end{cases}$$

Let π' and σ' be permutations in \mathcal{S}_{n-1} with element k removed from π and σ correspondingly, then $\mathbf{x}_{\pi'} = \mathbf{x}_{\sigma'}$, and hence $\pi' = \sigma'$. Therefore, the Kendall tau distance between σ and π is determined only by the location of element k in σ and π , which is at most $n - 1$. ■

Proof of Theorem 2: It is known that (see, e.g., [35, Lemma 4])

$$d_{\ell_1}(\mathbf{x}_{\pi_1}, \mathbf{x}_{\pi_2}) \leq d_\tau(\pi_1, \pi_2).$$

Furthermore, the proof of [35, Lemma 4] indicates that for any two permutation π_1 and π_2 with $k = d_{\mathbf{x}, \ell_1}(\pi_1, \pi_2)$, let $\sigma_0 \triangleq \pi_1$ and $\sigma_k \triangleq \pi_2$, then there exists a sequence of permutations $\sigma_1, \sigma_2, \dots, \sigma_{k-1}$ such that $d_{\mathbf{x}, \ell_1}(\sigma_i, \sigma_{i+1}) = 1$, $0 \leq i \leq k - 1$. Then

$$\begin{aligned} d_\tau(\pi_1, \pi_2) &\leq \sum_{i=0}^{k-1} d_\tau(\sigma_i, \sigma_{i+1}) \\ &\stackrel{(a)}{\leq} \sum_{i=0}^{k-1} (n-1) = (n-1)d_{\mathbf{x}, \ell_1}(\pi_1, \pi_2), \end{aligned}$$

where (a) is due to Lemma 19. ■

C. Proof of (13)

To prove (13), we analyze the mean and variance of the Kendall tau distance and inversion- ℓ_1 distance between a permutation in \mathcal{S}_n and a randomly selected permutation, in Lemma 20 and Lemma 21 respectively.

Lemma 20: For any $\pi \in \mathcal{S}_n$, let σ be a permutation chosen uniformly from \mathcal{S}_n , and $X_\tau \triangleq d_\tau(\pi, \sigma)$, then

$$\mathbb{E}[X_\tau] = \frac{n(n-1)}{4}, \quad (38)$$

$$\text{Var}[X_\tau] = \frac{n(2n+5)(n-1)}{72}. \quad (39)$$

Proof: Let σ' be another permutation chosen independently and uniformly from \mathcal{S}_n , then we have both $\pi\sigma^{-1}$ and $\sigma'\sigma^{-1}$ are uniformly distributed over \mathcal{S}_n .

Note that Kendall tau distance is right-invariant [22], then $d_\tau(\pi, \sigma) = d_\tau(\pi\sigma^{-1}, \text{Id})$ and $d_\tau(\sigma', \sigma) = d_\tau(\sigma'\sigma^{-1}, \text{Id})$ are identically distributed, and hence the result follows [8, Table 1] and [24, Sec. 5.1.1]. ■

Lemma 21: For any $\pi \in \mathcal{S}_n$, let σ be a permutation chosen uniformly from \mathcal{S}_n , and $X_{\mathbf{x}, \ell_1} \triangleq d_{\mathbf{x}, \ell_1}(\pi, \sigma)$, then

$$\begin{aligned} \mathbb{E}[X_{\mathbf{x}, \ell_1}] &> \frac{n(n-1)}{8}, \\ \text{Var}[X_{\mathbf{x}, \ell_1}] &< \frac{(n+1)(n+2)(2n+3)}{6}. \end{aligned}$$

Proof: It is not hard to see that when σ is a permutation chosen uniformly from \mathcal{S}_n , $\mathbf{x}_\sigma(i)$ is uniformly distributed in $[0 : i]$, $1 \leq i \leq n - 1$. Therefore, $X_{\mathbf{x}, \ell_1} = \sum_{i=1}^{n-1} |a_i - U_i|$, where $U_i \sim \text{Unif}([0 : i])$ and $a_i \triangleq \mathbf{x}_\pi(i)$. Let $V_i = |a_i - U_i|$, $m_1 = \min\{i - a_i, a_i\}$ and $m_2 = \max\{i - a_i, a_i\}$, then

$$\mathbb{P}[V_i = d] = \begin{cases} 1/(i+1) & d = 0 \\ 2/(i+1) & 1 \leq d \leq m_1 \\ 1/(i+1) & m_1 + 1 \leq d \leq m_2 \\ 0 & \text{otherwise.} \end{cases}$$

Hence,

$$\begin{aligned} \mathbb{E}[V_i] &= \sum_{d=1}^{m_1} d \frac{2}{i+1} + \sum_{d=m_1+1}^{m_2} d \frac{1}{i+1} \\ &= \frac{2(1+m_1)m_1 + (m_2+m_1+1)(m_2-m_1)}{2(i+1)} \\ &= \frac{1}{2(i+1)}(m_1^2 + m_2^2 + i) \\ &\geq \frac{1}{2(i+1)} \left(\frac{(m_1+m_2)^2}{2} + i \right) = \frac{i(i+2)}{4(i+1)} > \frac{i}{4}, \end{aligned}$$

$$\text{Var}[V_i] \leq \mathbb{E}[V_i^2] \leq \frac{2}{i+1} \sum_{d=0}^i d^2 \leq (i+1)^2.$$

Then,

$$\mathbb{E}[X_{\mathbf{x}, \ell_1}] = \sum_{i=1}^{n-1} \mathbb{E}[V_i] > \frac{n(n-1)}{8},$$

$$\text{Var}[X_{\mathbf{x}, \ell_1}] = \sum_{i=1}^{n-1} \text{Var}[V_i] < \frac{(n+1)(n+2)(2n+3)}{6}.$$

With Lemma 20 and Lemma 21, now we show that the event that a scaled version of the Kendall tau distance is larger than the inversion- ℓ_1 distance is unlikely.

Proof for (13): Let $c_2 = 1/3$, let $t = n^2/7$, then noting

$$\begin{aligned} t &= \mathbb{E}[c \cdot X_\tau] + |\Theta(\sqrt{n})| \text{Std}[X_\tau] \\ &= \mathbb{E}[X_{\mathbf{x}, \ell_1}] - |\Theta(\sqrt{n})| \text{Std}[X_{\mathbf{x}, \ell_1}], \end{aligned}$$

by Chebyshev inequality,

$$\begin{aligned} \mathbb{P}[c \cdot X_\tau > X_{\mathbf{x}, \ell_1}] &\leq \mathbb{P}[c \cdot X_\tau > t] + \mathbb{P}[X_{\mathbf{x}, \ell_1} < t] \\ &\leq O(1/n) + O(1/n) = O(1/n). \end{aligned}$$

The general case of $c_2 < 1/2$ can be proved similarly. ■

APPENDIX B

PROOFS ON RATE-DISTORTION FUNCTIONS

D. Proof of Theorem 3

Proof: Statement 1 follows from (9).

Statement 2 and 3 follow from Theorem 1. For statement 2, let the encoding mapping for the (n, D_n) source code in $\mathcal{X}(\mathcal{S}_n, d_{\ell_1})$ be f_n and the encoding mapping in $\mathcal{X}(\mathcal{S}_n, d_\tau)$ be g_n , then

$$g_n(\pi) = [f_n(\pi^{-1})]^{-1}$$

is a (n, D_n) source code in $\mathcal{X}(\mathcal{S}_n, d_\tau)$. The proof for Statement 3 is similar.

Statement 4 follow directly from (12). ■

E. Proof of Theorem 4

We prove Theorem 4 by achievability and converse.

1) *Achievability*: The achievability for all permutation spaces of interest under both *worst-case distortion* and *average-case distortion* are established via the explicit code constructions in Section V.

2) *Converse*: For the converse, we show by contradiction that under average-case distortion, if the rate is less than $1 - \delta$, then the average distortion is larger than D_n . Therefore, $\bar{R} \geq 1 - \delta$, and hence $\hat{R} \geq \bar{R} \geq 1 - \delta$.

When $\delta = 1$, $\bar{R} = \hat{R} = 0$. When $0 \leq \delta < 1$, for any $0 < \varepsilon < 1 - \delta$ and any codebook $\bar{\mathcal{C}}_n$ with size such that

$$\log |\bar{\mathcal{C}}_n| = (1 - \delta - \varepsilon)n \log n + O(n), \quad (40)$$

from (7), when $D_n = \Theta(n^{1+\delta})$ or $D_n = O(n)$,

$$\begin{aligned} N_{\ell_1}(2D_n) |\bar{\mathcal{C}}_n| &\leq N_\tau(2D_n) |\bar{\mathcal{C}}_n| \\ &\leq N_{\mathbf{x}, \ell_1}(2D_n) |\bar{\mathcal{C}}_n| \stackrel{(a)}{\leq} n!/2; \end{aligned}$$

when $D_n = \Theta(n^\delta)$ or $D_n = O(1)$,

$$N_{\ell_\infty}(2D_n) |\bar{\mathcal{C}}_n| \leq N_{\ell_1}(2D_n) |\bar{\mathcal{C}}_n| \leq n!/2$$

when n sufficiently large, where (a) follows from (35).

Therefore, given $\bar{\mathcal{C}}_n$, there exists at least $n!/2$ permutations in \mathcal{S}_n that has distortion larger than $2D_n$, and hence the average distortion w.r.t. uniform distribution over \mathcal{S}_n is larger than D_n .

Therefore, for any codebook with size indicated in (40), we have average distortion larger than D_n . Therefore, any (n, D_n) code must satisfy $\hat{R} \geq \bar{R} \geq 1 - \delta$.

APPENDIX C PROOFS ON MALLOWS MODEL

F. Proof of Lemma 11

Proof: When $q = 1$ the Mallows model reduces to the uniform distribution on the permutation space. When $q \neq 1$, let $X^n = [X_1, X_2, \dots, X_n]$ be the inversion vector, and denote a geometric random variable by G and a geometric random variable truncated at k by G_k . Define

$$E_k = \begin{cases} 0 & G \leq k \\ 1 & \text{o.w.,} \end{cases}$$

then $\mathbb{P}[E_k = 0] = Q_k = 1 - q^{k+1}$. Note

$$\begin{aligned} H(G_k, E) &= H(G|E_k) + H(E_k) \\ &= H(E_k|G) + H(G) \\ &= H(G) \end{aligned}$$

and

$$\begin{aligned} H(G|E_k) &= H(G|E_k = 0) Q_k \\ &\quad + H(G|E_k = 1) (1 - Q_k) \\ &= H(G_k) Q_k + H(G) (1 - Q_k), \end{aligned}$$

we have

$$H(G_k) = H_b(q)/(1 - q) - H_b(Q_k)/Q_k.$$

Then

$$\begin{aligned} H(\mathcal{M}(q)) &= \sum_{k=0}^{n-1} H(G_k) \\ &= \frac{nH_b(q)}{1 - q} - \sum_{k=1}^n \frac{H_b(q^k)}{1 - q^k}. \end{aligned}$$

It can be shown via algebraic manipulations that

$$\sum_{k=1}^n H_b(q^k) \leq \frac{2q - q^2}{(1 - q)^2} = \Theta(1),$$

therefore

$$H(\mathcal{M}(q)) = \frac{nH_b(q)}{1 - q} - \Theta(1).$$

G. Proof of Lemma 12

We first show an upper bound $K_n(k)$ (cf. (2) for definition), the number of permutations with k inversion in \mathcal{S}_n .

Lemma 22 (Bounds on $K_n(k)$): For $k = cn$,

$$K_n(k) \leq \frac{1}{\sqrt{2\pi nc/(1+c)}} 2^{n(1+c)H_b(1/(1+c))}.$$

Proof: By definition, $K_n(k)$ equals to the number of non-negative integer solutions of the equation $z_1 + z_2 + \dots + z_{n-1} = k$ with $0 \leq z_i \leq i, 1 \leq i \leq n-1$. Then similar to the derivations in the proof of Lemma 14,

$$K_n(k) < Q(n-1, k) = \binom{n+k-2}{k}.$$

Finally, applying the bound [27]

$$\binom{n}{pn} \leq \frac{2^{nH_b(p)}}{\sqrt{2\pi np(1-p)}}$$

completes the proof. ■

Proof of Lemma 12: Note

$$d_\tau(\sigma, \text{Id}) = d_{\mathbf{x}, \ell_1}(\sigma, \mathbf{0}).$$

Therefore,

$$\sum_{\sigma \in \mathcal{S}_n, d_\tau(\sigma, \text{Id}) \geq r_0} \mathbb{P}[\sigma] = \frac{1}{Z_q} \sum_{r=r_0}^{\binom{n}{2}} q^r K_n(r).$$

And Lemma 22 indicates for any $r = cn$,

$$q^r K_n(r) \leq \frac{2^{n[(1+c)H_b(\frac{1}{1+c}) - c \log_2 \frac{1}{q}]}}{\sqrt{2\pi nc/(1+c)}}.$$

Define

$$E(c, q) \triangleq \left[(1+c)H_b\left(\frac{1}{1+c}\right) - c \log_2 \frac{1}{q} \right],$$

then for any $\varepsilon > 0$, there exists c_0 such that for any $c \geq c_0(q)$, $E(c, q) < -\varepsilon$. Therefore, let $r_0 \geq c_0 n$,

$$\begin{aligned} \sum_{\sigma \in \mathcal{S}_n, d_\tau(\sigma, \text{Id}) \geq r_0} \mathbb{P}[\sigma] &\leq \frac{1}{\sqrt{2\pi nc/(1+c)}} \frac{1}{Z_q} \sum_{r=r_0}^{\binom{n}{2}} 2^{-n\varepsilon} \\ &\rightarrow 0 \end{aligned}$$

as $n \rightarrow \infty$. ■

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