Testing Identity of Structured Distributions

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Abstract

We study the question of identity testing for structured distributions. More precisely, given samples from a *structured* distribution q over $[n]$ and an explicit distribution p over $[n]$, we wish to distinguish whether $q = p$ versus q is at least ε-far from p, in L_1 distance. In this work, we present a unified approach that yields new, simple testers, with sample complexity that is information-theoretically optimal, for broad classes of structured distributions, including t-flat distributions, t-modal distributions, log-concave distributions, monotone hazard rate (MHR) distributions, and mixtures thereof.

1 Introduction

How many samples do we need to verify the identity of a distribution? This is arguably *the* single most fundamental question in statistical hypothesis testing [NP33], with Pearson's chi-squared test [Pea00] (and variants thereof) still being the method of choice used in practice. This question has also been extensively studied by the TCS community in the framework of *property testing* [RS96, GGR98]: Given sample access to an unknown distribution q over a finite domain $[n] := \{1, \ldots, n\}$, an explicit distribution p over $[n]$, and a parameter $\varepsilon > 0$, we want to distinguish between the cases that q and p are identical versus ε-far from each other in L_1 norm (statistical distance). Previous work on this problem focused on characterizing the sample size needed to test the identity of an arbitrary distribution of a given support size. After more than a decade of study, this "worst-case" regime is well-understood: there exists a computationally efficient estimator with sample complexity $O(\sqrt{n}/\varepsilon^2)$ [VV14] and a matching information-theoretic lower bound [Pan08].

While it is certainly a significant improvement over naive approaches and is tight in general, the bound of $\Theta(\sqrt{n})$ is still impractical, if the support size n is very large. We emphasize that the aforementioned sample complexity characterizes worst-case instances, and one might hope that drastically better results can be obtained for most natural settings. In contrast to this setting, in which we assume nothing about the structure of the unknown distribution q, in many cases we know a priori that the distribution q in question has some "nice structure". For example, we may have some qualitative information about the density q, e.g., it may be a mixture of a small number of log-concave distributions, or a multi-modal distribution with a bounded number of modes. The

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following question naturally arises: *Can we exploit the underlying structure in order to perform the desired statistical estimation task more efficiently?*

One would optimistically hope for the answer to the above question to be "YES." While this has been confirmed in several cases for the problem of *learning* (see e.g., [DDS12a, DDS12b, DDO+13, CDSS14]), relatively little work has been done for *testing* properties of structured distributions. In this paper, we show that this is indeed the case for the aforementioned problem of identity testing for a broad spectrum of natural and well-studied distribution classes. To describe our results in more detail, we will need some terminology.

Let C be a class of distributions over $[n]$. The problem of *identity testing for C* is the following: Given sample access to an unknown distribution $q \in C$, and an explicit distribution $p \in C$[1], we want to distinguish between the case that $q = p$ versus $\|q - p\|_1 \geq \varepsilon$. We emphasize that the sample complexity of this testing problem depends on the underlying class C, and we believe it is of fundamental interest to obtain efficient algorithms that are *sample optimal* for C. One approach to solve this problem is to learn q up to L_1 distance $\varepsilon/2$ and check that the hypothesis is $\varepsilon/2$-close to p. Thus, the sample complexity of identity testing for C is bounded from above by the sample complexity of *learning* (an arbitrary distribution in) C. It is natural to ask whether a better sample size bound could be achieved for the identity testing problem, since this task is, in some sense, less demanding than the task of learning.

In this work, we provide a comprehensive picture of the sample and computational complexities of identity testing for a broad class of structured distributions. More specifically, we propose a unified framework that yields new, simple, and *provably optimal* identity testers for various structured classes C; see Table 1 for an indicative list of distribution classes to which our framework applies. *Our approach relies on a single unified algorithm that we design, which yields highly efficient identity testers for many shape restricted classes of distributions.*

As an interesting byproduct, we establish that, for various structured classes C, identity testing for C is provably easier than learning. In particular, the sample bounds in the third column of Table 1 from [CDSS14] also apply for *learning* the corresponding class C, and are known to be information-theoretically optimal for the learning problem.

Our main result (see Theorem 1 and Proposition 2 in Section 2) can be phrased, roughly, as follows: *Let C be a class of univariate distributions such that any pair of distributions $p, q \in C$ have "essentially" at most k crossings, that is, points of the domain where $q - p$ changes its sign. Then, the identity problem for C can be solved with $O(\sqrt{k}/\varepsilon^2)$ samples. Moreover, this bound is information-theoretically optimal.*

By the term "essentially" we mean that a constant fraction of the contribution to $\|q - p\|_1$ is due to a set of k crossings – the actual number of crossings can be arbitrary. For example, if C is the class of t-piecewise constant distributions, it is clear that any two distributions in C have $O(t)$ crossings, which gives us the first line of Table 1. As a more interesting example, consider the class C of log-concave distributions over $[n]$. While the number of crossings between $p, q \in C$ can be $\Omega(n)$, it can be shown (see Lemma 17 in [CDSS14]) that the essential number of crossings is $k = \widetilde{O}(1/\sqrt{\varepsilon})$, which gives us the third line of the table. More generally, we obtain asymptotic improvements over the standard $O(\sqrt{n}/\varepsilon^2)$ bound for any class C such that the essential number of crossings is $k = o(n)$. This condition applies for any class C that can be well-approximated in L_1 distance by piecewise low-degree polynomials (see Corollary 3 for a precise statement).

1.1 Related and Prior Work

In this subsection we review the related literature and compare our results with previous work.

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[1] It is no loss of generality to assume that $p \in C$; otherwise the tester can output "NO" without drawing samples.

Class of Distributions over $[n]$	Our upper bound	Previous work
t-piecewise constant	$O(\sqrt{t}/\varepsilon^2)$	$O(t/\varepsilon^2)$ [CDSS14]
t-piecewise degree-d polynomial	$O\left(\sqrt{t(d+1)}/\varepsilon^2\right)$	$O\left(t(d+1)/\varepsilon^2\right)$ [CDSS14]
log-concave	$\widetilde{O}(1/\varepsilon^{9/4})$	$\widetilde{O}(1/\varepsilon^{5/2})$ [CDSS14]
k-mixture of log-concave	$\sqrt{k} \cdot \widetilde{O}(1/\varepsilon^{9/4})$	$\widetilde{O}(k/\varepsilon^{5/2})$ [CDSS14]
t-modal	$O(\sqrt{t\log(n)}/\varepsilon^{5/2})$	$O\left(\sqrt{t\log(n)}/\varepsilon^3 + t^2/\varepsilon^4\right)$ [DDS$^+$13]
k-mixture of t-modal	$O(\sqrt{kt\log(n)}/\varepsilon^{5/2})$	$O\left(\sqrt{kt\log(n)}/\varepsilon^3 + k^2t^2/\varepsilon^4\right)$ [DDS$^+$13]
monotone hazard rate (MHR)	$O(\sqrt{\log(n/\varepsilon)}/\varepsilon^{5/2})$	$O(\log(n/\varepsilon)/\varepsilon^3)$ [CDSS14]
k-mixture of MHR	$O(\sqrt{k\log(n/\varepsilon)}/\varepsilon^{5/2})$	$O(k\log(n/\varepsilon)/\varepsilon^3)$ [CDSS14]

Table 1: Algorithmic results for identity testing of various classes of probability distributions. The second column indicates the sample complexity of our general algorithm applied to the class under consideration. The third column indicates the sample complexity of the best previously known algorithm for the same problem.

Distribution Property Testing The area of distribution property testing, initiated in the TCS community by the work of Batu *et al.* [BFR$^+$00, BFR$^+$13], has developed into a very active research area with intimate connections to information theory, learning and statistics. The paradigmatic algorithmic problem in this area is the following: given sample access to an unknown distribution q over an n-element set, we want to determine whether q has some property or is "far" (in statistical distance or, equivalently, L_1 norm) from any distribution having the property. The overarching goal is to obtain a computationally efficient algorithm that uses as few samples as possible – certainly asymptotically fewer than the support size n, and ideally much less than that. See [GR00, BFR$^+$00, BFF$^+$01, Bat01, BDKR02, BKR04, Pan08, Val11, VV11, DDS$^+$13, ADJ$^+$11, LRR11, ILR12] for a sample of works and [Rub12] for a survey.

One of the first problems studied in this line of work is that of "identity testing against a known distribution": Given samples from an unknown distribution q and an explicitly given distribution p distinguish between the case that $q = p$ versus the case that q is ε-far from p in L_1 norm. The problem of *uniformity testing* – the special case of identity testing when p is the uniform distribution – was first considered by Goldreich and Ron [GR00] who, motivated by a connection to testing expansion in graphs, obtained a uniformity tester using $O(\sqrt{n}/\varepsilon^4)$ samples. Subsequently, Paninski gave the tight bound of $\Theta(\sqrt{n}/\varepsilon^2)$ [Pan08] for this problem. Batu *et al.* [BFF$^+$01] obtained an identity testing algorithm against an arbitrary explicit distribution with sample complexity $\tilde{O}(\sqrt{n}/\varepsilon^4)$. The tight bound of $\Theta(\sqrt{n}/\varepsilon^2)$ for the general identity testing problem was given only recently in [VV14].

Shape Restricted Statistical Estimation The area of inference under shape constraints – that is, inference about a probability distribution under the constraint that its probability density function (pdf) satisfies certain qualitative properties – is a classical topic in statistics starting with the pioneering work of Grenander [Gre56] on monotone distributions (see [BBBB72] for an early book on the topic). Various structural restrictions have been studied in the statistics literature, starting from monotonicity, unimodality, and concavity [Gre56, Bru58, Rao69, Weg70, HP76, Gro85, Bir87a, Bir87b, Fou97, CT04, JW09], and more recently focusing on structural restrictions such as log-concavity and k-monotonicity [BW07, DR09, BRW09, GW09, BW10, KM10].

Shape restricted inference is well-motivated in its own right, and has seen a recent surge of research activity in the statistics community, in part due to the ubiquity of structured distributions

in the natural sciences. Such structural constraints on the underlying distributions are sometimes direct consequences of the studied application problem (see e.g., Hampel [Ham87], or Wang *et al.* [WWW+05]), or they are a plausible explanation of the model under investigation (see e.g., [Reb05] and references therein for applications to economics and reliability theory). We also point the reader to the recent survey [Wal09] highlighting the importance of log-concavity in statistical inference. The hope is that, under such structural constraints, the quality of the resulting estimators may dramatically improve, both in terms of sample size and in terms of computational efficiency.

We remark that the statistics literature on the topic has focused primarily on the problem of *density estimation* or learning an unknown structured distribution. That is, given samples from a distribution q promised to belong to some distribution class C, we would like to output a hypothesis distribution that is a good approximation to q. In recent years, there has been a flurry of results in the TCS community on learning structured distributions, with a focus on both sample complexity and computational complexity, see [KMR+94, FOS05, BS10, KMV10, MV10, DDS12a, DDS12b, CDSS13, DDO+13, CDSS14] for some representative works.

Comparison with Prior Work In recent work, Chan, Diakonikolas, Servedio, and Sun [CDSS14] proposed a general approach to *learn* univariate probability distributions that are well approximated by piecewise polynomials. [CDSS14] obtained a computationally efficient and sample near-optimal algorithm to agnostically learn piecewise polynomial distributions, thus obtaining efficient estimators for various classes of structured distributions. For many of the classes C considered in Table 1 the best previously known sample complexity for the identity testing problem for C is identified with the sample complexity of the corresponding learning problem from [CDSS14]. We remark that the results of this paper apply to all classes C considered in [CDSS14], and are in fact more general as our condition (any $p, q \in C$ have a bounded number of "essential" crossings) subsumes the piecewise polynomial condition (see discussion before Corollary 3 in Section 2). At the technical level, in contrast to the learning algorithm of [CDSS14], which relies on a combination of linear programming and dynamic programming, our identity tester is simple and combinatorial.

In the context of property testing, Batu, Kumar, and Rubinfeld [BKR04] gave algorithms for the problem of identity testing of unimodal distributions with sample complexity $O(\log^3 n)$. More recently, Daskalakis, Diakonikolas, Servedio, Valiant, and Valiant [DDS+13] generalized this result to t-modal distributions obtaining an identity tester with sample complexity $O(\sqrt{t\log(n)}/\varepsilon^3 + t^2/\varepsilon^4)$. We remark that for the class of t-modal distributions our approach yields an identity tester with sample complexity $O(\sqrt{t\log(n)}/\varepsilon^{5/2})$, matching the lower bound of [DDS+13]. Moreover, our work yields sample optimal identity testing algorithms not only for t-modal distributions, but for a broad spectrum of structured distributions via a unified approach.

It should be emphasized that the main ideas underlying this paper are very different from those of [DDS+13]. The algorithm of [DDS+13] is based on the fact from [Bir87a] that any t-modal distribution is ε-close in L_1 norm to a piecewise constant distribution with $k = O(t \cdot \log(n)/\varepsilon)$ intervals. Hence, if the location and the width of these k "flat" intervals were known in advance, the problem would be easy: The algorithm could just test identity between the "reduced" distributions supported on these k intervals, thus obtaining the optimal sample complexity of $O(\sqrt{k}/\varepsilon^2) = O(\sqrt{t\log(n)}/\varepsilon^{5/2})$. To circumvent the problem that this decomposition is not known a priori, [DDS+13] start by drawing samples from the unknown distribution q to construct such a decomposition. There are two caveats with this strategy: First, the number of samples used to achieve this is $\Omega(t^2)$ and the number of intervals of the constructed decomposition is significantly larger than k, namely $k' = \Omega(k/\varepsilon)$. As a consequence, the sample complexity of identity testing for the reduced distributions on support k' is $\Omega(\sqrt{k'}/\varepsilon^2) = \Omega(\sqrt{t\log(n)}/\varepsilon^3)$.

In conclusion, the approach of [DDS+13] involves constructing an *adaptive* interval decomposi-

tion of the domain followed by a single application of an identity tester to the reduced distributions over those intervals. At a high-level our novel approach works as follows: We consider *several oblivious* interval decompositions of the domain (i.e., without drawing any samples from q) and apply a "reduced" identity tester for *each* such decomposition. While it may seem surprising that such an approach can be optimal, our algorithm and its analysis exploit a certain strong property of uniformity testers, namely their performance guarantee with respect to the L_2 *norm*. See Section 2 for a detailed explanation of our techniques.

Finally, we comment on the relation of this work to the recent paper [VV14]. In [VV14], Valiant and Valiant study the sample complexity of the identity testing problem as a function of the explicit distribution. In particular, [VV14] makes no assumptions about the structure of the unknown distribution q, and characterizes the sample complexity of the identity testing problem as a function of the known distribution p. The current work provides a unified framework to exploit structural properties of the unknown distribution q, and yields sample optimal identity testers for various shape restrictions. Hence, the results of this paper are orthogonal to the results of [VV14].

2 Our Results and Techniques

2.1 Basic Definitions

We start with some notation that will be used throughout this paper. We consider discrete probability distributions over $[n] := \{1, \ldots, n\}$, which are given by probability density functions $p : [n] \to [0, 1]$ such that $\sum_{i=1}^{n} p_i = 1$, where p_i is the probability of element i in distribution p. By abuse of notation, we will sometimes use p to denote the distribution with density function p_i. We emphasize that we view the domain $[n]$ as an ordered set. Throughout this paper we will be interested in structured distribution families that respect this ordering.

The L_1 (resp. L_2) norm of a distribution is identified with the L_1 (resp. L_2) norm of the corresponding density function, i.e., $\|p\|_1 = \sum_{i=1}^{n} |p_i|$ and $\|p\|_2 = \sqrt{\sum_{i=1}^{n} p_i^2}$. The L_1 (resp. L_2) distance between distributions p and q is defined as the L_1 (resp. L_2) norm of the vector of their difference, i.e., $\|p - q\|_1 = \sum_{i=1}^{n} |p_i - q_i|$ and $\|p - q\|_2 = \sqrt{\sum_{i=1}^{n} (p_i - q_i)^2}$. We will denote by U_n the uniform distribution over $[n]$.

Interval partitions and $\mathcal{A}_k$-distance Fix a partition of $[n]$ into disjoint intervals $\mathcal{I} := (I_i)_{i=1}^{\ell}$. For such a collection $\mathcal{I}$ we will denote its cardinality by $|\mathcal{I}|$, i.e., $|\mathcal{I}| = \ell$. For an interval $J \subseteq [n]$, we denote by $|J|$ its cardinality or length, i.e., if $J = [a, b]$, with $a \leq b \in [n]$, then $|J| = b - a + 1$. The *reduced distribution* $p_r^{\mathcal{I}}$ corresponding to p and $\mathcal{I}$ is the distribution over $[\ell]$ that assigns the ith "point" the mass that p assigns to the interval I_i; i.e., for $i \in [\ell]$, $p_r^{\mathcal{I}}(i) = p(I_i)$.

We now define a distance metric between distributions that will be crucial for this paper. Let $\mathfrak{J}_k$ be the collection of all partitions of $[n]$ into k intervals, i.e., $\mathcal{I} \in \mathfrak{J}_k$ if and only if $\mathcal{I} = (I_i)_{i=1}^{k}$ is a partition of $[n]$ into intervals $I_1, \ldots, I_k$. For $p, q : [n] \to [0, 1]$ and $k \in \mathbb{Z}_+$, $2 \leq k \leq n$, we define the $\mathcal{A}_k$-distance between p and q by

$$\|p - q\|_{\mathcal{A}_k} \stackrel{\text{def}}{=} \max_{\mathcal{I}=(I_i)_{i=1}^{k} \in \mathfrak{J}_k} \sum_{i=1}^{k} |p(I_i) - q(I_i)| = \max_{\mathcal{I} \in \mathfrak{J}_k} \|p_r^{\mathcal{I}} - q_r^{\mathcal{I}}\|_1.$$

We remark that the $\mathcal{A}_k$-distance between distributions[2] is well-studied in probability theory and statistics. Note that for any pair of distributions $p, q : [n] \to [0, 1]$, and any $k \in \mathbb{Z}_+$ with $2 \leq k \leq n$,

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[2]We note that the definition of $\mathcal{A}_k$-distance in this work is slightly different than [DL01, CDSS14], but is easily seen to be essentially equivalent. In particular, [CDSS14] considers the quantity $\max_{S \in \mathcal{S}_k} |p(S) - q(S)|$, where $\mathcal{S}_k$ is the collection of all unions of at most k intervals in $[n]$. It is a simple exercise to verify that $\|p - q\|_{\mathcal{A}_k} \leq$

we have that $\|p - q\|_{\mathcal{A}_k} \leq \|p - q\|_1$, and the two metrics are identical for $k = n$. Also note that $\|p - q\|_{\mathcal{A}_2} = 2 \cdot d_{\mathrm{K}}(p, q)$, where d_{K} is the Kolmogorov metric (i.e., the L_∞ distance between the CDF's).

Discussion The well-known *Vapnik-Chervonenkis (VC) inequality* (see e.g., [DL01, p.31]) provides the information-theoretically optimal sample size to *learn* an arbitrary distribution q over $[n]$ in this metric. In particular, it implies that $m = \Omega(k/\varepsilon^2)$ iid draws from q suffice in order to learn q within $\mathcal{A}_k$-distance ε (with probability at least $9/10$). This fact has recently proved useful in the context of learning structured distributions: By exploiting this fact, Chan, Diakonikolas, Servedio, and Sun [CDSS14] recently obtained computationally efficient and near-sample optimal algorithms for learning various classes of structured distributions *with respect to the L_1 distance*.

It is thus natural to ask the following question: What is the sample complexity of *testing* properties of distributions with respect to the $\mathcal{A}_k$-distance? Can we use property testing algorithms in this metric to obtain sample-optimal testing algorithms for interesting classes of structured distributions *with respect to the L_1 distance*? In this work we answer both questions in the affirmative for the problem of identity testing.

2.2 Our Results

Our main result is an optimal algorithm for the identity testing problem under the $\mathcal{A}_k$-distance metric:

Theorem 1 (Main). *Given $\varepsilon > 0$, an integer k with $2 \leq k \leq n$, sample access to a distribution q over $[n]$, and an explicit distribution p over $[n]$, there is a computationally efficient algorithm which uses $O(\sqrt{k}/\varepsilon^2)$ samples from q, and with probability at least $2/3$ distinguishes whether $q = p$ versus $\|q - p\|_{\mathcal{A}_k} \geq \varepsilon$. Additionally, $\Omega(\sqrt{k}/\varepsilon^2)$ samples are information-theoretically necessary.*

The information-theoretic sample lower bound of $\Omega(\sqrt{k}/\varepsilon^2)$ can be easily deduced from the known lower bound of $\Omega(\sqrt{n}/\varepsilon^2)$ for uniformity testing over $[n]$ under the L_1 norm [Pan08]. Indeed, if the underlying distribution q over $[n]$ is piecewise constant with k pieces, and p is the uniform distribution over $[n]$, we have $\|q - p\|_{\mathcal{A}_k} = \|q - p\|_1$. Hence, our $\mathcal{A}_k$-uniformity testing problem in this case is at least as hard as L_1-uniformity testing over support of size k.

The proof of Theorem 1 proceeds in two stages: In the first stage, we reduce the $\mathcal{A}_k$ identity testing problem to $\mathcal{A}_k$ uniformity testing without incurring any loss in the sample complexity. In the second stage, we use an optimal L_2 *uniformity* tester as a black-box to obtain an $O(\sqrt{k}/\varepsilon^2)$ sample algorithm for $\mathcal{A}_k$ uniformity testing. We remark that the L_2 uniformity tester is not applied to the distribution q directly, but to a sequence of reduced distributions $q_r^{\mathcal{I}}$, for an appropriate collection of interval partitions $\mathcal{I}$. See Section 2.3 for a detailed intuitive explanation of the proof.

We remark that an application of Theorem 1 for $k = n$, yields a sample optimal L_1 identity tester (for an arbitrary distribution q), giving a new algorithm matching the recent tight upper bound in [VV14]. Our new L_1 identity tester is arguable simpler and more intuitive, as it only uses an L_2 uniformity tester in a black-box manner.

We show that Theorem 1 has a wide range of applications to the problem of L_1 identity testing for various classes of natural and well-studied structured distributions. At a high level, the main message of this work is that the $\mathcal{A}_k$ distance can be used to characterize the sample complexity of L_1 identity testing for broad classes of structured distributions. The following simple proposition underlies our approach:

$2 \cdot \max_{S \in \mathcal{S}_k} |p(S) - q(S)| = \|p - q\|_{\mathcal{A}_{2k+1}}$, which implies that the two definitions are equivalent up to constant factors for the purpose of both upper and lower bounds.

Proposition 2. *For a distribution class C over $[n]$ and $\varepsilon > 0$, let $k = k(C, \varepsilon)$ be the smallest integer such that for any $f_1, f_2 \in C$ it holds that $\|f_1 - f_2\|_1 \leq \|f_1 - f_2\|_{\mathcal{A}_k} + \varepsilon/2$. Then there exists an L_1 identity testing algorithm for C using $O(\sqrt{k}/\varepsilon^2)$ samples.*

The proof of the proposition is straightforward: Given sample access to $q \in C$ and an explicit description of $p \in C$, we apply the $\mathcal{A}_k$-identity testing algorithm of Theorem 1 for the value of k in the statement of the proposition, and error $\varepsilon' = \varepsilon/2$. If $q = p$, the algorithm will output "YES" with probability at least $2/3$. If $\|q - p\|_1 \geq \varepsilon$, then by the condition of Proposition 2 we have that $\|q - p\|_{\mathcal{A}_k} \geq \varepsilon'$, and the algorithm will output "NO" with probability at least $2/3$. Hence, as long as the underlying distribution satisfies the condition of Proposition 2 for a value of $k = o(n)$, Theorem 1 yields an asymptotic improvement over the sample complexity of $\Theta(\sqrt{n}/\varepsilon^2)$.

We remark that the value of k in the proposition is a natural complexity measure for the difference between two probability density functions in the class C. It follows from the definition of the $\mathcal{A}_k$ distance that this value corresponds to the number of "essential" crossings between f_1 and f_2 – i.e., the number of crossings between the functions f_1 and f_2 that significantly affect their L_1 distance. Intuitively, the number of essential crossings – as opposed to the domain size – is, in some sense, the "right" parameter to characterize the sample complexity of L_1 identity testing for C. As we explain below, the upper bound implied by the above proposition is information-theoretically optimal for a wide range of structured distribution classes C.

More specifically, our framework can be applied to all structured distribution classes C that can be well-approximated in L_1 distance by *piecewise low-degree polynomials*. We say that a distribution p over $[n]$ is *t-piecewise degree-d* if there exists a partition of $[n]$ into t intervals such that p is a (discrete) degree-d polynomial within each interval. Let $\mathcal{P}_{t,d}$ denote the class of all t-piecewise degree-d distributions over $[n]$. We say that a distribution class C is *ε-close in L_1* to $\mathcal{P}_{t,d}$ if for any $f \in C$ there exists $p \in \mathcal{P}_{t,d}$ such that $\|f - p\|_1 \leq \varepsilon$. It is easy to see that any pair of distributions $p, q \in \mathcal{P}_{t,d}$ have at most $2t(d+1)$ crossings, which implies that $\|p - q\|_{\mathcal{A}_k} = \|p - q\|_1$, for $k = 2t(d+1)$ (see e.g., Proposition 6 in [CDSS14]). We therefore obtain the following:

Corollary 3. *Let C be a distribution class over $[n]$ and $\varepsilon > 0$. Consider parameters $t = t(C, \varepsilon)$ and $d = d(C, \varepsilon)$ such that C is $\varepsilon/4$-close in L_1 to $\mathcal{P}_{t,d}$. Then there exists an L_1 identity testing algorithm for C using $O(\sqrt{t(d+1)}/\varepsilon^2)$ samples.*

Note that any pair of values (t, d) satisfying the condition above suffices for the conclusion of the corollary. Since our goal is to minimize the sample complexity, for a given class C, we would like to apply the corollary for values t and d satisfying the above condition and are such that the product $t(d+1)$ is minimized. The appropriate choice of these values is crucial, and is based on properties of the underlying distribution family. Observe that the sample bound of $O(\sqrt{t(d+1)}/\varepsilon^2)$ is tight in general, as follows by selecting $C = \mathcal{P}_{t,d}$. This can be deduced from the general lower bound of $\Omega(\sqrt{n}/\varepsilon^2)$ for uniformity testing, and the fact that for $n = t(d+1)$, any distribution over support $[n]$ can be expressed as a t-piecewise degree-d distribution.

The concrete testing results of Table 1 are obtained from Corollary 3 by using known existential approximation theorems [Bir87a, CDSS13, CDSS14] for the corresponding structured distribution classes. In particular, we obtain efficient identity testers, in most cases with provably optimal sample complexity, for all the structured distribution classes studied in [CDSS13, CDSS14] in the context of learning. Perhaps surprisingly, our upper bounds are tight not only for the class of piecewise polynomials, but also for the specific shape restricted classes of Table 1. The corresponding lower bounds for specific classes are either known from previous work (as e.g., in the case of t-modal distributions [DDS+13]) or can be obtained using standard constructions.

Finally, we remark that the results of this paper can be appropriately generalized to the setting of testing the identity of continuous distributions over the real line. More specifically, Theorem 1

also holds for probability distributions over $\mathbb{R}$. (The only additional assumption required is that the explicitly given continuous pdf p can be efficiently integrated up to any additive accuracy.) In fact, the proof for the discrete setting extends almost verbatim to the continuous setting with minor modifications. It is easy to see that both Proposition 2 and Corollary 3 hold for the continuous setting as well.

2.3 Our Techniques

We now provide a detailed intuitive explanation of the ideas that lead to our main result, Theorem 1. Given sample access to a distribution q and an explicit distribution p, we want to test whether $q = p$ versus $\|q - p\|_{\mathcal{A}_k} \geq \varepsilon$. By definition we have that $\|q - p\|_{\mathcal{A}_k} = \max_{\mathcal{I}} \|q_r^{\mathcal{I}} - p_r^{\mathcal{I}}\|_1$. So, if the "optimal" partition $\mathcal{J}^* = (J_i^*)_{j=1}^k$ maximizing this expression was known a priori, the problem would be easy: Our algorithm could then consider the reduced distributions $q_r^{\mathcal{J}^*}$ and $p_r^{\mathcal{J}^*}$, which are supported on sets of size k, and call a standard L_1-identity tester to decide whether $q_r^{\mathcal{J}^*} = p_r^{\mathcal{J}^*}$ versus $\|q_r^{\mathcal{J}^*} - p_r^{\mathcal{J}^*}\|_1 \geq \varepsilon$. (Note that for any given partition $\mathcal{I}$ of $[n]$ into intervals and any distribution q, given sample access to q one can simulate sample access to the reduced distribution $q_r^{\mathcal{I}}$.) The difficulty, of course, is that the optimal k-partition is *not fixed*, as it depends on the unknown distribution q, thus it is not available to the algorithm. Hence, a more refined approach is necessary.

Our starting point is a new, simple reduction of the general problem of identity testing to its special case of uniformity testing. The main idea of the reduction is to appropriately "stretch" the domain size, using the explicit distribution p, in order to transform the identity testing problem between q and p into a uniformity testing problem for a (different) distribution q' (that depends on q and p). To show correctness of this reduction we need to show that it preserves the $\mathcal{A}_k$ distance, and that we can sample from q' given samples from q.

We now proceed with the details. Since p is given explicitly in the input, we assume for simplicity that each p_i is a rational number, hence there exists some (potentially large) $N \in \mathbb{Z}_+$ such that $p_i = \alpha_i/N$, where $\alpha_i \in \mathbb{Z}_+$ and $\sum_{i=1}^n \alpha_i = N$.[3] Given sample access to q and an explicit p over $[n]$, we construct an instance of the uniformity testing problem as follows: Let p' be the uniform distribution over $[N]$ and let q' be the distribution over $[N]$ obtained from q by subdividing the probability mass of q_i, $i \in [n]$, equally among α_i new consecutive points. It is clear that this reduction preserves the $\mathcal{A}_k$ distance, i.e., $\|q - p\|_{\mathcal{A}_k} = \|q' - p'\|_{\mathcal{A}_k}$. The only remaining task is to show how to simulate sample access to q', given samples from q. Given a sample i from q, our sample for q' is selected uniformly at random from the corresponding set of α_i many new points. Hence, we have reduced the problem of identity testing between q and p in $\mathcal{A}_k$ distance, to the problem of uniformity testing of q' in $\mathcal{A}_k$ distance. Note that this reduction is also computationally efficient, as it only requires $O(n)$ pre-computation to specify the new intervals.

For the rest of this section, we focus on the problem of $\mathcal{A}_k$ uniformity testing. For notational convenience, we will use q to denote the unknown distribution and p to denote the uniform distribution over $[n]$. The rough idea is to consider an appropriate collection of interval partitions of $[n]$ and call a standard L_1-uniformity tester for each of these partitions. To make such an approach work and give us a *sample optimal* algorithm for our $\mathcal{A}_k$-uniformity testing problem we need to use a subtle and strong property of uniformity testing, namely its performance guarantee under the L_2 norm. We elaborate on this point below.

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[3]We remark that this assumption is not necessary: For the case of irrational p_i's we can approximate them by rational numbers $\widetilde{p}_i$ up to sufficient accuracy and proceed with the approximate distribution $\widetilde{p}$. This approximation step does not preserve perfect completeness; however, we point out that our testers have some mild robustness in the completeness case, which suffices for all the arguments to go through.

For any partition $\mathcal{I}$ of $[n]$ into k intervals by definition we have that $\|q_r^{\mathcal{I}} - p_r^{\mathcal{I}}\|_1 \leq \|q - p\|_{\mathcal{A}_k}$. Therefore, if $q = p$, we will also have $q_r^{\mathcal{I}} = p_r^{\mathcal{I}}$. The issue is that $\|q_r^{\mathcal{I}} - p_r^{\mathcal{I}}\|_1$ can be much smaller than $\|q - p\|_{\mathcal{A}_k}$; in fact, it is not difficult to construct examples where $\|q - p\|_{\mathcal{A}_k} = \Omega(1)$ and $\|q_r^{\mathcal{I}} - p_r^{\mathcal{I}}\|_1 = 0$. In particular, it is possible for the points where q is larger than p, and where it is smaller than p to cancel each other out within each interval in the partition, thus making the partition useless for distinguishing q from p. In other words, if the partition $\mathcal{I}$ is not "good", we may not be able to detect any existing discrepancy. A simple, but suboptimal, way to circumvent this issue is to consider a partition $\mathcal{I}'$ of $[n]$ into $k' = \Theta(k/\varepsilon)$ intervals of the same length. Note that each such interval will have probability mass $1/k' = \Theta(\varepsilon/k)$ under the uniform distribution p. If the constant in the big-Θ is appropriately selected, say $k' = 10k/\varepsilon$, it is not hard to show that $\|q_r^{\mathcal{I}'} - p_r^{\mathcal{I}'}\|_1 \geq \|q - p\|_{\mathcal{A}_k} - \varepsilon/2$; hence, we will necessarily detect a large discrepancy for the reduced distribution. By applying the optimal L_1 uniformity tester this approach will require $\Omega(\sqrt{k'}/\varepsilon^2) = \Omega(\sqrt{k}/\varepsilon^{2.5})$ samples.

A key tool that is essential in our analysis is a strong property of uniformity testing. An optimal L_1 uniformity tester for q can distinguish between the uniform distribution and the case that $\|q - p\|_1 \geq \varepsilon$ using $O(\sqrt{n}/\varepsilon^2)$ samples. However, a stronger guarantee is possible: With the *same* sample size, we can distinguish the uniform distribution from the case that $\|q - p\|_2 \geq \varepsilon/\sqrt{n}$. We emphasize that such a strong L_2 guarantee is specific to uniformity testing, and is provably not possible for the general problem of identity testing. In previous work, Goldreich and Ron [GR00] gave such an L_2 guarantee for uniformity testing, but their algorithm uses $O(\sqrt{n}/\varepsilon^4)$ samples. Paninski's $O(\sqrt{n}/\varepsilon^2)$ uniformity tester works for the L_1 norm, and it is not known whether it achieves the desired L_2 property. As one of our main tools we show the following L_2 guarantee, which is optimal as a function of n and ε:

Theorem 4. *Given $0 < \varepsilon, \delta < 1$ and sample access to a distribution q over $[n]$, there is an algorithm* Test-Uniformity-$L_2(q, n, \varepsilon, \delta)$ *which uses $m = O\left((\sqrt{n}/\varepsilon^2) \cdot \log(1/\delta)\right)$ samples from q, runs in time linear in its sample size, and with probability at least $1 - \delta$ distinguishes whether $q = U_n$ versus $\|p - q\|_2 \geq \varepsilon/\sqrt{n}$.*

To prove Theorem 4 we show that a variant of Pearson's chi-squared test [Pea00] – which can be viewed as a special case of the recent "chi-square type" testers in [CDVV14, VV14] – has the desired L_2 guarantee. While this tester has been (implicitly) studied in [CDVV14, VV14], and it is known to be sample optimal with respect to the L_1 norm, it has not been previously analyzed for the L_2 norm. The novelty of Theorem 4 lies in the tight analysis of the algorithm under the L_2 distance, and is presented in Appendix A.

Armed with Theorem 4 we proceed as follows: We consider a set of $j_0 = O(\log(1/\varepsilon))$ different partitions of the domain $[n]$ into intervals. For $0 \leq j < j_0$ the partition $\mathcal{I}^{(j)}$ consists of $\ell_j \stackrel{\text{def}}{=} |\mathcal{I}^{(j)}| = k \cdot 2^j$ many intervals $I_i^{(j)}$, $i \in [\ell_j]$, i.e., $\mathcal{I}^{(j)} = (I_i^{(j)})_{i=1}^{\ell_j}$. For a fixed value of j, all intervals in $\mathcal{I}^{(j)}$ have the same length, or equivalently, the same probability mass *under the uniform distribution*. Then, for any fixed $j \in [j_0]$, we have $p(I_i^{(j)}) = 1/(k \cdot 2^j)$ for all $i \in [\ell_j]$. (Observe that, by our aforementioned reduction to the uniform case, we may assume that the domain size n is a multiple of $k2^{j_0}$, and thus that it is possible to evenly divide into such intervals of the same length).

Note that if $q = p$, then for all $0 \leq j < j_0$, it holds $q_r^{\mathcal{I}^{(j)}} = p_r^{\mathcal{I}^{(j)}}$. Recalling that all intervals in $\mathcal{I}^{(j)}$ have the same probability mass *under p*, it follows that $p_r^{\mathcal{I}^{(j)}} = U_{\ell_j}$, i.e., $p_r^{\mathcal{I}^{(j)}}$ is the uniform distribution over its support. So, if $q = p$, for any partition we have $q_r^{\mathcal{I}^{(j)}} = U_{\ell_j}$. Our main structural result (Lemma 6) is a robust inverse lemma: *If q is far from uniform in $\mathcal{A}_k$ distance then, for at least one of the partitions $\mathcal{I}^{(j)}$, the reduced distribution $q_r^{\mathcal{I}^{(j)}}$ will be far from uniform in L_2 distance*. The quantitative version of this statement is quite subtle. In particular, we start

from the assumption of being ε-far in $\mathcal{A}_k$ distance and can only deduce "far" in L_2 distance. This is absolutely critical for us to be able to obtain the optimal sample complexity.

The key insight for the analysis comes from noting that the optimal partition separating q from p in $\mathcal{A}_k$ distance cannot have too many parts. Thus, if the "highs" and "lows" cancel out over some small intervals, they must be very large in order to compensate for the fact that they are relatively narrow. Therefore, when p and q differ on a smaller scale, their L_2 discrepancy will be greater, and this compensates for the fact that the partition detecting this discrepancy will need to have more intervals in it.

In Section 3 we present our sample optimal uniformity tester under the $\mathcal{A}_k$ distance, thereby establishing Theorem 1.

3 Testing Uniformity under the $\mathcal{A}_k$-norm

Algorithm Test-Uniformity-$\mathcal{A}_k(q, n, \varepsilon)$
Input: sample access to a distribution q over $[n]$, $k \in \mathbb{Z}_+$ with $2 \leq k \leq n$, and $\varepsilon > 0$.
Output: "YES" if $q = U_n$; "NO" if $\|q - U_n\|_{\mathcal{A}_k} \geq \varepsilon$.

1. Draw a sample S of size $m = O(\sqrt{k}/\varepsilon^2)$ from q.

2. Fix $j_0 \in \mathbb{Z}_+$ such that $j_0 \stackrel{\text{def}}{=} \lceil \log_2(1/\varepsilon) \rceil + O(1)$. Consider the collection $\{\mathcal{I}^{(j)}\}_{j=0}^{j_0-1}$ of j_0 partitions of $[n]$ into intervals; the partition $\mathcal{I}^{(j)} = (I_i^{(j)})_{i=1}^{\ell_j}$ consists of $\ell_j = k \cdot 2^j$ many intervals with $p(I_i^{(j)}) = 1/(k \cdot 2^j)$, where $p \stackrel{\text{def}}{=} U_n$.

3. For $j = 0, 1, \ldots, j_0 - 1$:

   (a) Consider the reduced distributions $q_r^{\mathcal{I}^{(j)}}$ and $p_r^{\mathcal{I}^{(j)}} \equiv U_{\ell_j}$. Use the sample S to simulate samples to $q_r^{\mathcal{I}^{(j)}}$.

   (b) Run Test-Uniformity-$L_2(q_r^{\mathcal{I}^{(j)}}, \ell_j, \varepsilon_j, \delta_j)$ for $\varepsilon_j = C \cdot \varepsilon \cdot 2^{3j/8}$ for $C > 0$ a sufficiently small constant and $\delta_j = 2^{-j}/6$, i.e., test whether $q_r^{\mathcal{I}^{(j)}} = U_{\ell_j}$ versus $\|q_r^{\mathcal{I}^{(j)}} - U_{\ell_j}\|_2 > \gamma_j \stackrel{\text{def}}{=} \varepsilon_j/\sqrt{\ell_j}$.

4. If all the testers in Step 3(b) output "YES", then output "YES"; otherwise output "NO".

Proposition 5. *The algorithm* Test-Uniformity-$\mathcal{A}_k(q, n, \varepsilon)$, *on input a sample of size* $m = O(\sqrt{k}/\varepsilon^2)$ *drawn from a distribution q over $[n]$, $\varepsilon > 0$ and an integer k with $2 \leq k \leq n$, correctly distinguishes the case that $q = U_n$ from the case that $\|q - U_n\|_{\mathcal{A}_k} \geq \varepsilon$, with probability at least $2/3$.*

Proof. First, it is straightforward to verify the claimed sample complexity, as the algorithm only draws samples in Step 1. Note that the algorithm uses the same set of samples S for all testers in Step 3(b). By Theorem 4, the tester Test-Uniformity-$L_2(q_r^{\mathcal{I}^{(j)}}, \ell_j, \varepsilon_j, \delta_j)$, on input a set of $m_j = O((\sqrt{\ell_j}/\varepsilon_j^2) \cdot \log(1/\delta_j))$ samples from $q_r^{\mathcal{I}^{(j)}}$ distinguishes the case that $q_r^{\mathcal{I}^{(j)}} = U_{\ell_j}$ from the case that $\|q_r^{\mathcal{I}^{(j)}} - U_{\ell_j}\|_2 \geq \gamma_j \stackrel{\text{def}}{=} \varepsilon_j/\sqrt{\ell_j}$ with probability at least $1 - \delta_j$. From our choice of parameters it can be verified that $\max_j m_j \leq m = O(\sqrt{k}/\varepsilon^2)$, hence we can use the same sample S as input to these testers for all $0 \leq j \leq j_0 - 1$. In fact, it is easy to see that $\sum_{j=0}^{j_0-1} m_j = O(m)$, which implies that the overall algorithm runs in sample-linear time. Since each tester in Step 3(b) has error probability δ_j, by a union bound over all $j \in \{0, \ldots, j_0 - 1\}$, the total error probability

is at most $\sum_{j=0}^{j_0-1} \delta_j \leq (1/6) \cdot \sum_{j=0}^{\infty} 2^{-j} = 1/3$. Therefore, with probability at least $2/3$ all the testers in Step 3(b) succeed. We will henceforth condition on this "good" event, and establish the completeness and soundness properties of the overall algorithm under this conditioning.

We start by establishing completeness. If $q = p = U_n$, then for any partition $\mathcal{I}^{(j)}$, $0 \leq j \leq j_0 - 1$, we have that $q_r^{\mathcal{I}^{(j)}} = p_r^{\mathcal{I}^{(j)}} = U_{\ell_j}$. By our aforementioned conditioning, all testers in Step 3(b) will output "YES", hence the overall algorithm will also output "YES", as desired.

We now proceed to establish the soundness of our algorithm. Assuming that $\|q - p\|_{\mathcal{A}_k} \geq \varepsilon$, we want to show that the algorithm Test-Uniformity-$\mathcal{A}_k(q, n, \varepsilon)$ outputs "NO" with probability at least $2/3$. Towards this end, we prove the following structural lemma:

Lemma 6. *There exists a constant $C > 0$ such that the following holds: If $\|q - p\|_{\mathcal{A}_k} \geq \varepsilon$, there exists $j \in \mathbb{Z}_+$ with $0 \leq j \leq j_0 - 1$ such that $\|q_r^{\mathcal{I}^{(j)}} - U_{\ell_j}\|_2^2 \geq \gamma_j^2 \overset{\text{def}}{=} \varepsilon_j^2/\ell_j = C^2 \cdot (\varepsilon^2/k) \cdot 2^{-j/4}$.*

Given the lemma, the soundness property of our algorithm follows easily. Indeed, since all testers Test-Uniformity-$L_2(q_r^{\mathcal{I}^{(j)}}, \ell_j, \varepsilon_j, \delta_j)$ of Step 3(b) are successful by our conditioning, Lemma 6 implies that at least one of them outputs "NO", hence the overall algorithm will output "NO". $\square$

The proof of Lemma 6 in its full generality is quite technical. For the sake of the intuition, in the following subsection (Section 3.1) we provide a proof of the lemma for the important special case that the unknown distribution q is promised to be *k-flat*, i.e., piecewise constant with k pieces. This setting captures many of the core ideas and, at the same time, avoids some of the necessary technical difficulties of the general case. Finally, in Section 3.2 we present our proof for the general case.

3.1 Proof of Structural Lemma: k-flat Case

For this special case we will prove the lemma for $C = 1/80$. Since q is k-flat there exists a partition $\mathcal{I}^* = (I_j^*)_{j=1}^k$ of $[n]$ into k intervals so that q is constant within each such interval. This in particular implies that $\|q - p\|_{\mathcal{A}_k} = \|q - p\|_1$, where $p \overset{\text{def}}{=} U_n$. For $J \in \mathcal{I}^*$ let us denote by q_J the value of q within interval J, that is, for all $j \in [k]$ and $i \in I_j^*$ we have $q_i = q_{I_j^*}$. For notational convenience, we sometimes use p_J to denote the value of $p = U_n$ within interval J. By assumption we have that $\|q - p\|_1 = \sum_{j=1}^k |I_j^*| \cdot |q_{I_j^*} - 1/n| \geq \varepsilon$.

Throughout the proof, we work with intervals $I_j^* \in \mathcal{I}^*$ such that $q_{I_j^*} < 1/n$. We will henceforth refer to such intervals as *troughs* and will denote by $\mathcal{T} \subseteq [k]$ the corresponding set of indices, i.e., $\mathcal{T} = \{j \in [k] \mid q_{I_j^*} < 1/n\}$. For each trough $J \in \{I_j^*\}_{j \in \mathcal{T}}$ we define its *depth* as $\mathbf{depth}(J) = (p_J - q_J)/p_J = n \cdot (1/n - q_J)$ and its *width* as $\mathbf{width}(J) = p(J) = (1/n) \cdot |J|$. Note that the width of J is identified with the probability mass that the uniform distribution assigns to it. The *discrepancy* of a trough J is defined by $\mathbf{Discr}(J) = \mathbf{depth}(J) \cdot \mathbf{width}(J) = |J| \cdot (1/n - q_J)$ and corresponds to the contribution of J to the L_1 distance between q and p.

It follows from Scheffe's identity that half of the contribution to $\|q - p\|_1$ comes from troughs, namely $\|q - p\|_1^{\mathcal{T}} \overset{\text{def}}{=} \sum_{j \in \mathcal{T}} \mathbf{Discr}(I_j^*) = (1/2) \cdot \|q - p\|_1 \geq \varepsilon/2$. An important observation is that we may assume that all troughs have *width* at most $1/k$ at the cost of potentially doubling the total number of intervals. Indeed, it is easy to see that we can artificially subdivide "wider" troughs so that each new trough has width at most $1/k$. This process comes at the expense of at most doubling the number of troughs. Let us denote by $\{\widetilde{I}_j\}_{j \in \mathcal{T}'}$ this set of (new) troughs, where $|\mathcal{T}'| \leq 2k$ and each $\widetilde{I}_j$ is a subset of some I_i^*, $i \in \mathcal{T}$. We will henceforth deal with the set of troughs $\{\widetilde{I}_j\}_{j \in \mathcal{T}'}$ each

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of width at most $1/k$. By construction, it is clear that

$$\|q - p\|_1^{\widetilde{\mathcal{T}}'} \overset{\text{def}}{=} \sum_{j \in \mathcal{T}'} \mathbf{Discr}(\widetilde{I}_j) = \|q - p\|_1^{\mathcal{T}} \geq \varepsilon/2. \tag{1}$$

At this point we note that we can essentially ignore troughs $J \in \{\widetilde{I}_j\}_{j \in \mathcal{T}'}$ with small discrepancy. Indeed, the total contribution of intervals $J \in \{\widetilde{I}_j\}_{j \in \mathcal{T}'}$ with $\mathbf{Discr}(J) \leq \varepsilon/20k$ to the LHS of (1) is at most $|\mathcal{T}'| \cdot (\varepsilon/20k) \leq 2k \cdot (\varepsilon/20k) = \varepsilon/10$. Let $\mathcal{T}^*$ be the subset of $\mathcal{T}'$ corresponding to troughs with discrepancy at least $\varepsilon/20k$, i.e., $j \in \mathcal{T}^*$ if and only if $j \in \mathcal{T}'$ and $\mathbf{Discr}(\widetilde{I}_j) \geq \varepsilon/20k$. Then, we have that

$$\|q - p\|_1^{\mathcal{T}^*} \overset{\text{def}}{=} \sum_{j \in \mathcal{T}^*} \mathbf{Discr}(\widetilde{I}_j) \geq 2\varepsilon/5. \tag{2}$$

Observe that for any interval J it holds $\mathbf{Discr}(J) \leq \mathbf{width}(J)$. Note that this part of the argument depends critically on considering only troughs. Hence, for $j \in \mathcal{T}^*$ we have that

$$\varepsilon/(20k) \leq \mathbf{width}(\widetilde{I}_j) \leq 1/k. \tag{3}$$

Thus far we have argued that a constant fraction of the contribution to $\|q - p\|_1$ comes from troughs whose width satisfies (3). Our next crucial claim is that each such trough must have a "large" overlap with one of the intervals $I_i^{(j)}$ considered by our algorithm Test-Uniformity-$\mathcal{A}_k$. In particular, consider a trough $J \in \{\widetilde{I}_j\}_{j \in \mathcal{T}^*}$. We claim that there exists $j \in \{0, \ldots, j_0 - 1\}$ and $i \in [\ell_j]$ such that $|I_i^{(j)}| \geq |J|/4$ and so that $I_i^{(j)} \subseteq J$. To see this we first pick a j so that $\mathbf{width}(J)/2 > 2^{-j}/k \geq \mathbf{width}(J)/4$. Since the $I_i^{(j)}$ have width less than half that of J, J must intersect at least three of these intervals. Thus, any but the two outermost such intervals will be entirely contained within J, and furthermore has width $2^j/k \geq \mathbf{width}(J)/4$.

Since the interval $L \in \mathcal{I}^{(j+1)}$ is a "domain point" for the reduced distribution $q_r^{\mathcal{I}^{(j+1)}}$, the L_1 error between $q_r^{\mathcal{I}^{(j+1)}}$ and $U_{\ell_{j+1}}$ incurred by this element is at least $\frac{1}{4} \cdot \mathbf{Discr}(J)$, and the corresponding L_2^2 error is at least $\frac{1}{16} \cdot (\mathbf{Discr}(J))^2 \geq \frac{\varepsilon}{320k} \cdot \mathbf{Discr}(J)$, where the inequality follows from the fact that $\mathbf{Discr}(J) \geq \varepsilon/(20k)$. Hence, we have that

$$\|q_r^{\mathcal{I}^{(j+1)}} - U_{\ell_{j+1}}\|_2^2 \geq \varepsilon/(320k) \cdot \mathbf{Discr}(J). \tag{4}$$

As shown above, for every trough $J \in \{\widetilde{I}_j\}_{j \in \mathcal{T}^*}$ there exists a level $j \in \{0, \ldots, j_0 - 1\}$ such that (4) holds. Hence, summing (4) over all levels we obtain

$$\sum_{j=0}^{j_0-1} \|q_r^{\mathcal{I}^{(j+1)}} - U_{\ell_{j+1}}\|_2^2 \geq \varepsilon/(320k) \cdot \sum_{j \in \mathcal{T}^*} \mathbf{Discr}(\widetilde{I}_j) \geq \varepsilon^2/(800k), \tag{5}$$

where the second inequality follows from (2). Note that

$$\sum_{j=0}^{j_0-1} \gamma_j^2 \leq \sum_{j=0}^{j_0-1} \frac{\varepsilon^2 \cdot 2^{3j/4}}{80^2 \cdot k2^j} = \frac{\varepsilon^2}{6400k} \sum_{j=0}^{j_0-1} 2^{-j/4} < \varepsilon^2/(800k).$$

Therefore, by the above, we must have that $\|q_r^{\mathcal{I}^{(j+1)}} - U_{\ell_{j+1}}\|_2^2 > \gamma_j^2$ for some $0 \leq j \leq j_0 - 1$. This completes the proof of Lemma 6 for the special case of q being k-flat.

3.2 Proof of Structural Lemma: General Case

To prove the general version of our structural result for the $\mathcal{A}_k$ distance, we will need to choose an appropriate value for the universal constant C. We show that it is sufficient to take $C \leq 5 \cdot 10^{-6}$. (While we have not attempted to optimize constant factors, we believe that a more careful analysis will lead to substantially better constants.)

A useful observation is that our Test-Uniformity-$\mathcal{A}_k$ algorithm only distinguishes which of the intervals of $\mathcal{I}^{(j_0-1)}$ each of our samples lies in, and can therefore equivalently be thought of as a uniformity tester for the reduced distribution $q_r^{\mathcal{I}^{(j_0-1)}}$. In order to show that it suffices to consider only this restricted sample set, we claim that

$$\|q_r^{\mathcal{I}^{(j_0-1)}} - U_{\ell_{j_0-1}}\|_{\mathcal{A}_k} \geq \|p - q\|_{\mathcal{A}_k} - \varepsilon/2.$$

In particular, these $\mathcal{A}_k$ distances would be equal if the dividers of the optimal partition for q were all on boundaries between intervals of $\mathcal{I}^{(j_0-1)}$. If this was not the case though, we could round the endpoint of each trough inward to the nearest such boundary (note that we can assume that the optimal partition has no two adjacent troughs). This increases the discrepancy of each trough by at most $2k \cdot 2^{-j_0}$, and thus for $j_0 - \log_2(1/\varepsilon)$ a sufficiently large universal constant, the total discrepancy decreases by at most $\varepsilon/2$.

Thus, we have reduced ourselves to the case where $n = 2^{j_0-1} \cdot k$ and have argued that it suffices to show that our algorithm works to distinguish $\mathcal{A}_k$-distance in this setting with $\varepsilon_j = 10^{-5} \cdot \varepsilon \cdot 2^{3j/8}$.

The analysis of the completeness and the soundness of the tester is identical to Proposition 5. The only missing piece is the proof of Lemma 6, which we now restate for the sake of convenience:

Lemma 7. *If $\|q - p\|_{\mathcal{A}_k} \geq \varepsilon$, there exists some $j \in \mathbb{Z}_+$ with $0 \leq j \leq j_0 - 1$ such that*

$$\|q_r^{\mathcal{I}^{(j)}} - U_{\ell_j}\|_2^2 \geq \gamma_j^2 := \varepsilon_j^2/\ell_j = 10^{-10} 2^{-j/4} \varepsilon^2/k.$$

The analysis of the general case here is somewhat more complicated than the special case for q being k-flat case that was presented in the previous section. This is because it is possible for one of the intervals J in the optimal partition (i.e., the interval partition $\mathcal{I}^* \in \mathfrak{J}_k$ maximizing $\|q_r^{\mathcal{I}} - q_r^{\mathcal{I}}\|_1$ in the definition of the $\mathcal{A}_k$ distance) to have large overlap with an interval I that our algorithm considers – that is, $I \in \cup_{j=0}^{j_0-1} \mathcal{I}^{(j)}$ – without having $q(I)$ and $p(I)$ differ substantially. Note that the unknown distribution q is not guaranteed to be constant within such an interval J, and in particular the difference $q - p$ does not necessarily preserve its sign within J.

To deal with this issue, we note that there are two possibilities for an interval J in the optimal partition: Either one of the intervals $I_i^{(j)}$ (considered by our algorithm) of size at least $|J|/2$ has discrepancy comparable to J, or the distribution q differs from p even more substantially on one of the intervals separating the endpoints of $I_i^{(j)}$ from the endpoints of J. Therefore, either an interval contained within this will detect a large L_2 error, or we will need to again pass to a subinterval. To make this intuition rigorous, we will need a mechanism for detecting where this recursion will terminate. To handle this formally, we introduce the following definition:

Definition 8. For $p = U_n$ and q an arbitrary distribution over $[n]$, we define the *scale-sensitive-L_2 distance* between q and p to be

$$\|q - p\|_{[k]}^2 \stackrel{\text{def}}{=} \max_{\mathcal{I} = (I_1, \dots, I_r) \in \mathbf{W}_{1/k}} \sum_{i=1}^r \frac{\mathbf{Discr}^2(I_i)}{\mathbf{width}^{1/8}(I_i)}$$

where $\mathbf{W}_{1/k}$ is the collection of all interval partitions of $[n]$ into intervals of width at most $1/k$.

The notion of the scale-sensitive-L_2 distance will be a useful intermediate tool in our analysis. The rough idea of the definition is that the optimal partition will be able to detect the correctly sized intervals for our tester to notice. (It will act as an analogue of the partition into the intervals where q is constant for the k-flat case.)

The first thing we need to show is that if q and p have large $\mathcal{A}_k$ distance then they also have large scale-sensitive-L_2 distance. Indeed, we have the following lemma:

Lemma 9. *For $p = U_n$ and q an arbitrary distribution over $[n]$, we have that*

$$\|q - p\|_{[k]}^2 \geq \frac{\|q - p\|_{\mathcal{A}_k}^2}{(2k)^{7/8}}.$$

Proof. Let $\varepsilon = \|q - p\|_{\mathcal{A}_k}^2$. Consider the optimal $\mathcal{I}^*$ in the definition of the $\mathcal{A}_k$ distance. As in our analysis for the k-flat case, by further subdividing intervals of width more than $1/k$ into smaller ones, we can obtain a new partition, $\mathcal{I}' = (I_i')_{i=1}^s$, of cardinality $s \leq 2k$ all of whose parts have width at most $1/k$. Furthermore, we have that $\sum_i \mathbf{Discr}(I_i') \geq \varepsilon$. Using this partition to bound from below $\|q - p\|_{[k]}^2$, by Cauchy-Schwarz we obtain that

$$
\begin{aligned}
\|q - p\|_{[k]}^2 &\geq \sum_i \frac{\mathbf{Discr}^2(I_i')}{\mathbf{width}(I_i')^{1/8}} \\
&\geq \frac{\left(\sum_i \mathbf{Discr}(I_i')\right)^2}{\sum_i \mathbf{width}(I_i')^{1/8}} \\
&\geq \frac{\varepsilon^2}{2k(1/(2k))^{1/8}} \\
&= \frac{\varepsilon^2}{(2k)^{7/8}}.
\end{aligned}
$$

$\square$

The second important fact about the scale-sensitive-L_2 distance is that if it is large then one of the partitions considered in our algorithm will produce a large L_2 error.

Proposition 10. *Let $p = U_n$ be the uniform distribution and q a distribution over $[n]$. Then we have that*

$$\|q - p\|_{[k]}^2 \leq 10^8 \sum_{j=0}^{j_0-1} \sum_{i=1}^{2^j \cdot k} \frac{\mathbf{Discr}^2(I_i^{(j)})}{\mathbf{width}^{1/8}(I_i^{(j)})}. \tag{6}$$

Proof. Let $\mathcal{J} \in \mathbf{W}_{1/k}$ be the optimal partition used when computing the scale-sensitive-L_2 distance $\|q - p\|_{[k]}$. In particular, it is a partition into intervals of width at most $1/k$ so that $\sum_i \frac{\mathbf{Discr}^2(J_i)}{\mathbf{width}(J_i)^{1/8}}$ is maximized. To prove Equation Eq. (6), we prove a notably stronger claim. In particular, we will prove that for each interval $J_\ell \in \mathcal{J}$

$$\frac{\mathbf{Discr}^2(J_\ell)}{\mathbf{width}^{1/8}(J_\ell)} \leq 10^8 \sum_{j=0}^{j_0-1} \sum_{i:I_i^{(j)} \subset J_\ell} \frac{\mathbf{Discr}^2(I_i^{(j)})}{\mathbf{width}^{1/8}(I_i^{(j)})}. \tag{7}$$

Summing over ℓ would then yield $\|q - p\|_{[k]}^2$ on the left hand side and a strict subset of the terms from Equation Eq. (6) on the right hand side. From here on, we will consider only a single interval J_ℓ. For notational convenience, we will drop the subscript and merely call it J.

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First, note that if $|J| \leq 10^8$, then this follows easily from considering just the sum over $j = j_0 - 1$. Then, if $t = |J|$, J is divided into t intervals of size one. The sum of the discrepancies of these intervals equals the discrepancy of J, and thus, the sum of the squares of the discrepancies is at least $\mathbf{Discr}^2(J)/t$. Furthermore, the widths of these subintervals are all smaller than the width of J by a factor of t. Thus, in this case the sum of the right hand side of Equation Eq. (7) is at least $1/t^{7/8} \geq \frac{1}{10^7}$ of the left hand side.

Otherwise, if $|J| > 10^8$, we can find a j so that $\mathbf{width}(J)/10^8 < 1/(2^j \cdot k) \leq 2 \cdot \mathbf{width}(J)/10^8$. We claim that in this case Equation Eq. (7) holds even if we restrict the sum on the right hand side to this value of j. Note that J contains at most 10^8 intervals of $\mathcal{I}^{(j)}$, and that it is covered by these intervals plus two narrower intervals on the ends. Call these end-intervals R_1 and R_2. We claim that $\mathbf{Discr}(R_i) \leq \mathbf{Discr}(J)/3$. This is because otherwise it would be the case that

$$\frac{\mathbf{Discr}^2(R_i)}{\mathbf{width}^{1/8}(R_i)} > \frac{\mathbf{Discr}^2(J)}{\mathbf{width}^{1/8}(J)}.$$

(This is because $(1/3)^2 \cdot (2/10^8)^{-1/8} > 1$.) This is a contradiction, since it would mean that partitioning J into R_i and its complement would improve the sum defining $\|q - p\|_{[k]}$, which was assumed to be maximum. This in turn implies that the sum of the discrepancies of the $I_i^{(j)}$ contained in J must be at least $\mathbf{Discr}(J)/3$, so the sum of their squares is at least $\mathbf{Discr}^2(J)/(9 \cdot 10^8)$. On the other hand, each of these intervals is narrower than J by a factor of at least $10^8/2$, thus the appropriate sum of $\frac{\mathbf{Discr}^2(I_i^{(j)})}{\mathbf{width}^{1/8}(I_i^{(j)})}$ is at least $\frac{\mathbf{Discr}^2(J)}{10^8 \mathbf{width}^{1/8}(J)}$. This completes the proof. □

We are now ready to prove Lemma 7.

Proof. If $\|q - p\|_{\mathcal{A}_k} \geq \varepsilon$ we have by Lemma 9 that

$$\|q - p\|_{[k]}^2 \geq \frac{\varepsilon^2}{(2k)^{7/8}}.$$

By Proposition 10, this implies that

$$\frac{\varepsilon^2}{(2k)^{7/8}} \leq 10^8 \sum_{j=0}^{j_0-1} \sum_{i=1}^{2^j \cdot k} \frac{\mathbf{Discr}^2(I_i^{(j)})}{\mathbf{width}^{1/8}(I_i^{(j)})}$$

$$= 10^8 \sum_{j=0}^{j_0-1} (2^j k)^{1/8} \|q^{\mathcal{I}^{(j)}} - U_{\ell_j}\|_2^2.$$

Therefore,

$$\sum_{j=0}^{j_0-1} 2^{j/8} \|q^{\mathcal{I}^{(j)}} - U_{\ell_j}\|_2^2 \geq 5 \cdot 10^{-9} \varepsilon^2/k. \tag{8}$$

On the other hand, if $\|q^{\mathcal{I}^{(j)}} - U_{\ell_j}\|_2^2$ were at most $10^{-10} 2^{-j/4} \varepsilon^2/k$ for each j, then the sum above would be at most

$$10^{-10} \varepsilon^2/k \sum_j 2^{-j/8} < 5 \cdot 10^{-9} \varepsilon^2/k.$$

This would contradict Equation Eq. (8), thus proving that $\|q^{\mathcal{I}^{(j)}} - U_{\ell_j}\|_2^2 \geq 10^{-10} 2^{-j/4} \varepsilon^2/k$ for at least one j, proving Lemma 7. □

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4 Conclusions and Future Work

In this work we designed a computationally efficient algorithm for the problem of identity testing against a known distribution, which yields sample optimal bounds for a wide range of natural and important classes of structured distributions. A natural direction for future work is to generalize our results to the problem of identity testing between two unknown structured distributions. What is the optimal sample complexity in this more general setting? We emphasize that new ideas are required for this problem, as the algorithm and analysis in this work crucially exploit the a priori knowledge of the explicit distribution.

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Appendix: Omitted Proofs

A   A Useful Primitive: Testing Uniformity in L_2 norm

In this section, we give an algorithm for uniformity testing with respect to the L_2 distance, thereby establishing Theorem 4. The algorithm Test-Uniformity-$L_2(q, n, \varepsilon)$ described below draws $O(\sqrt{n}/\varepsilon^2)$ samples from a distribution q over $[n]$ and distinguishes between the cases that $q = U_n$ versus $\|q - U_n\|_2 > \varepsilon/\sqrt{n}$ with probability at least $2/3$. Repeating the algorithm $O(\log(1/\delta))$ times and taking the majority answer results in a confidence probability of $1 - \delta$, giving the desired algorithm Test-Uniformity-$L_2(q, n, \varepsilon, \delta)$ of Theorem 4.

Our estimator is a variant of Pearson's chi-squared test [Pea00], and can be viewed as a special case of the recent "chi-square type" testers in [CDVV14, VV14]. We remark that, as follows from the Cauchy-Schwarz inequality, the same estimator distinguishes the uniform distribution from any distribution q such that $\|q - U_n\|_1 > \varepsilon$, i.e., algorithm Test-Uniformity-$L_2(q, n, \varepsilon)$ is an optimal uniformity tester for the L_1 norm. The L_2 guarantee we prove here is new, is strictly stronger than the aforementioned L_1 guarantee, and is crucial for our purposes in Section 3.

For $\lambda \geq 0$, we denote by $\mathrm{Poi}(\lambda)$ the Poisson distribution with parameter λ. In our algorithm below, we employ the standard "Poissonization" approach: namely, we assume that, rather than drawing m independent samples from a distribution, we first select m' from $\mathrm{Poi}(m)$, and then draw m' samples. This Poissonization makes the number of times different elements occur in the

sample independent, with the distribution of the number of occurrences of the i-th domain element distributed as $\text{Poi}(mq_i)$, simplifying the analysis. As $\text{Poi}(m)$ is tightly concentrated about m, we can carry out this Poissonization trick without loss of generality at the expense of only sub-constant factors in the sample complexity.

Algorithm Test-Uniformity-$L_2(q, n, \varepsilon)$
Input: sample access to a distribution q over $[n]$, and $\varepsilon > 0$.
Output: "YES" if $q = U_n$; "NO" if $\|q - U_n\|_2 \geq \varepsilon/\sqrt{n}$.

1. Draw $m' \sim \text{Poi}(m)$ iid samples from q.

2. Let X_i be the number of occurrences of the ith domain elements in the sample from q

3. Define $Z = \sum_{i=1}^{n}(X_i - m/n)^2 - X_i$.

4. If $Z \geq 4m/\sqrt{n}$ return "NO"; otherwise, return "YES".

The following theorem characterizes the performance of the above estimator:

Theorem 11. *For any distribution q over $[n]$ the above algorithm distinguishes the case that $q = U_n$ from the case that $\|q - U_n\|_2 \geq \varepsilon/\sqrt{n}$ when given $O(\sqrt{n}/\varepsilon^2)$ samples from q with probability at least $2/3$.*

Proof. Define $Z_i = (X_i - m/n)^2 - X_i$. Since X_i is distributed as $\text{Poi}(mq_i)$, $\mathbb{E}[Z_i] = m^2 \Delta_i^2$, where $\Delta_i := 1/n - q_i$. By linearity of expectation we can write $\mathbb{E}[Z] = \sum_{i=1}^{n} \mathbb{E}[Z_i] = m^2 \cdot \sum_{i=1}^{n} \Delta_i^2$. Similarly we can calculate

$$\text{Var}[Z_i] = 2m^2(\Delta_i - 1/n)^2 + 4m^3(1/n - \Delta_i)\Delta_i^2.$$

Since the X_i's (and hence the Z_i's) are independent, it follows that $\text{Var}[Z] = \sum_{i=1}^{n} \text{Var}[Z_i]$.

We start by establishing completeness. Suppose $q = U_n$. We will show that $\Pr[Z \geq 4m/\sqrt{n}] \leq 1/3$. Note that in this case $\Delta_i = 0$ for all $i \in [n]$, hence $\mathbb{E}[Z] = 0$ and $\text{Var}[Z] = 2m^2/n$. Chebyshev's inequality implies that

$$\Pr[Z \geq 4m/\sqrt{n}] = \Pr\left[Z \geq (2\sqrt{2})\sqrt{\text{Var}[Z]}\right] \leq (1/8) < 2/3$$

as desired.

We now proceed to prove soundness of the tester. Suppose that $\|q - U_n\|_2 \geq \frac{\varepsilon}{\sqrt{n}}$. In this case we will show that $\Pr[Z \leq 4m/\sqrt{n}] \leq 1/3$. Note that Chebyshev's inequality implies that

$$\Pr\left[Z \leq \mathbb{E}[Z] - 2\sqrt{\text{Var}[Z]}\right] \leq 1/4.$$

It thus suffices to show that $\mathbb{E}[Z] \geq 8m/\sqrt{n}$ and $\mathbb{E}[Z]^2 \geq 16\text{Var}[Z]$. Establishing the former inequality is easy. Indeed,

$$\mathbb{E}[Z] = m^2 \cdot \|q - U_n\|_2^2 \geq m^2 \cdot (\varepsilon^2/n) \geq 8m/\sqrt{n}$$

for $m \geq 8\sqrt{n}/\varepsilon^2$.

Proving the latter inequality requires a more detailed analysis. We will show that for a sufficiently large constant $C > 0$, if $m \geq C\sqrt{n}/\varepsilon^2$ we will have

$$\text{Var}[Z] \ll \mathbb{E}[Z]^2.$$

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Ignoring multiplicative constant factors, we equivalently need to show that

$$m^2 \cdot \left(\sum_{i=1}^{n} \left(\Delta_i^2 - 2\Delta_i/n \right) + 1/n \right) + m^3 \sum_{i=1}^{n} \left(\Delta_i^2/n + \Delta_i^3 \right) \ll m^4 \left(\sum_{i=1}^{n} \Delta_i^2 \right)^2.$$

To prove the desired inequality, it suffices to bound from above the absolute value of each of the five terms of the LHS separately. For the first term we need to show that $m^2 \cdot \sum_{i=1}^{n} \Delta_i^2 \ll m^4 \cdot \left(\sum_{i=1}^{n} \Delta_i^2 \right)^2$ or equivalently

$$m \gg 1/\|q - U_n\|_2. \tag{9}$$

Since $\|q - U_n\|_2 \geq \varepsilon/\sqrt{n}$, the RHS of (9) is bounded from above by $\sqrt{n}/\varepsilon$, hence (9) holds true for our choice of m.

For the second term we want to show that $\sum_{i=1}^{n} |\Delta_i| \ll m^2 n \cdot \left(\sum_{i=1}^{n} \Delta_i^2 \right)^2$. Recalling that $\sum_{i=1}^{n} |\Delta_i| \leq \sqrt{n} \cdot \sqrt{\sum_{i=1}^{n} \Delta_i^2}$, as follows from the Cauchy-Schwarz inequality, it suffices to show that $m^2 \gg (1/\sqrt{n}) \cdot 1/(\sum_{i=1}^{n} \Delta_i^2)^{3/2}$ or equivalently

$$m \gg \frac{1}{n^{1/4}} \cdot \frac{1}{\|q - U_n\|_2^{3/2}}. \tag{10}$$

Since $\|q - U_n\|_2 \geq \varepsilon/\sqrt{n}$, the RHS of (10) is bounded from above by $\sqrt{n}/\varepsilon^{3/2}$, hence (10) is also satisfied.

For the third term we want to argue that $m^2/n \ll m^4 \cdot \left(\sum_{i=1}^{n} \Delta_i^2 \right)^2$ or

$$m \gg \frac{1}{n^{1/2}} \cdot \frac{1}{\|q - U_n\|_2^2}, \tag{11}$$

which holds for our choice of m, since the RHS is bounded from above by $\sqrt{n}/\varepsilon^2$.

Bounding the fourth term amounts to showing that $(m^3/n) \sum_{i=1}^{n} \Delta_i^2 \ll m^4 \left(\sum_{i=1}^{n} \Delta_i^2 \right)^2$ which can be rewritten as

$$m \gg \frac{1}{n} \cdot \frac{1}{\|q - U_n\|_2^2}, \tag{12}$$

and is satisfied since the RHS is at most $1/\varepsilon^2$.

Finally, for the fifth term we want to prove that $m^3 \cdot \sum_{i=1}^{n} |\Delta_i|^3 \ll m^4 \cdot \left(\sum_{i=1}^{n} \Delta_i^2 \right)^2$ or that $\sum_{i=1}^{n} |\Delta_i|^3 \ll m \cdot \left(\sum_{i=1}^{n} \Delta_i^2 \right)^2$. From Jensen's inequality it follows that $\sum_{i=1}^{n} |\Delta_i|^3 \leq \left(\sum_{i=1}^{n} |\Delta_i|^2 \right)^{3/2}$; hence, it is sufficient to show that $\left(\sum_{i=1}^{n} |\Delta_i|^2 \right)^{3/2} \ll m \cdot \left(\sum_{i=1}^{n} \Delta_i^2 \right)^2$ or

$$m \gg \frac{1}{\|q - U_n\|_2}. \tag{13}$$

Since $\|q - U_n\|_2 \geq \varepsilon/\sqrt{n}$ the above RHS is at most $\sqrt{n}/\varepsilon$ and (13) is satisfied. This completes the soundness proof and the proof of Theorem 11. $\qquad\square$