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Learning Simple Auctions

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Abstract

We present a general framework for proving polynomial sample complexity bounds for the problem of learning from samples the best auction in a class of "simple" auctions. Our framework captures the most prominent examples of "simple" auctions, including anonymous and non-anonymous item and bundle pricings, with either a single or multiple buyers. The first step of the framework is to show that the set of auction allocation rules have a low-dimensional representation. The second step shows that, across the subset of auctions that share the same allocations on a given set of samples, the auction revenue varies in a low-dimensional way. Our results imply that in typical scenarios where it is possible to compute a near-optimal simple auction with a known prior, it is also possible to compute such an auction with an unknown prior, given a polynomial number of samples.

1. Introduction

We consider multi-item (or "combinatorial") auctions, where a set of goods is sold to a set of n bidders. Such an auction accepts bids as input and decides who gets what and who pays what. The mapping from bids to an assignment of the goods to the bidders is called the *allocation rule* of the auction. The mapping from bids to payments is called the *payment rule* of the auction. The sum of the payments is the *revenue* of the auction.

We consider the problem of choosing an auction to maximize the seller's revenue. To reason about the outcome of an auction, we need a (standard) model of how bidders behave. We assume that each bidder i has a *valuation* v_i specifying her willingness to pay for each subset (or "bundle") of goods, and strives to maximize her "quasilinear utility," meaning her valuation for the items obtained minus the total price paid. The valuation v_i is known to bidder i but not to the seller (or the other buyers). We focus on "truthful" or "dominant-strategy incentive-compatible" auctions, where every bidder can maximize her utility by reporting her true valuation to the seller (no matter what the other bidders do). For example, a second-price auction for a single item (e.g., eBay) is truthful, while a first-price single-item auction is not (since bidders have an incentive to underbid). Because we confine attention to truthful auctions, we henceforth use bids and valuations interchangeably.

The standard economic approach to designing revenue-maximizing auctions assumes that all information unknown to the designer is drawn from some prior distribution, about which the designer has perfect information. With this "perfect" prior in hand, the designer fine-tunes an auction to optimize for her expected revenue with respect to the unknown information. Three related difficulties arise when trying to use this design pattern in practice. First, for any particular setting, it is unlikely that the designer can actually formulate a perfect prior over the market's hidden information. Second, if the market designer has an imperfect prior, it is possible that her optimal auction has overfit to this prior and will have poor revenue when run on the (similar) true prior. Finally, the optimal auction for a particular prior can be quite complicated and unintuitive.

These obstacles can be addressed in a principled manner by designing auctions as a function of several *samples* (for us, bidders' valuations) drawn from an unknown distribution, with the goal of earning high expected revenue on a fresh draw from the same distribution. It is reasonable to expect that experienced sellers have previous records of the bids made by previous participants in the market.

How many samples are necessary to determine an auction with a revenue guarantee that generalizes, in the sense that the auction is guaranteed to perform as well on future draws from a distribution as it does on past samples? The answer depends upon the complexity of the set of auctions available to the seller. The more complex the class of auctions, the lower the class's "representation error" (the higher the revenue the seller might be able to extract using an auction in the class); on the other hand, a more complex class of auctions will have higher "generalization error" (the loss in revenue from optimizing over the sample rather than the true prior) for a fixed sample size.

The idea of choosing an auction from samples dovetails nicely with an ongoing research agenda in the auction and mechanism design community, where "simplicity" is often taken as a design goal for its own sake, in both "single-parameter" (Hartline and Roughgarden, 2009) and "multi-parameter" (Chawla et al., 2007, 2010; Babaioff et al., 2014; Rubinstein and Weinberg, 2015) auctions.[1] Recent work (Morgenstern and Roughgarden, 2015) proposed the use of a class's pseudo-dimension as a formal notion of simplicity for single-parameter auctions, and proves for general single-parameter settings there exist classes of auctions with small representation error (the class always contains a nearly-optimal auction) *and* small pseudo-dimension or generalization error (a polynomial-sized sample suffices to learn a nearly-optimal auction from that class).

In this work, we give a general framework for bounding the pseudo-dimension of classes of multi-parameter auctions. Our results imply polynomial sample complexity bounds for revenue maximization for all of the aforementioned classes of "simple" auctions.

For instance, one concrete example of a class of well-studied "simple" multi-parameter auctions comes from Babaioff et al. (2014). Consider a single bidder whose valuation is *additive* over k items: there is a vector $v \in \mathbb{R}^k$ such that the bidder's valuation for a bundle $B \subseteq [k]$ is $\sum_{j \in B} v_j$. An *item pricing* is defined by a vector $\mathbf{p} \in \mathbb{R}^k$, and offers the agent each bundle B for the price $\sum_{j \in B} \mathbf{p}_j$. A *grand bundle pricing* is defined by a single real number $q \in \mathbb{R}$ and offers only the bundle $B = [k]$ for the price q. When a single additive buyer's valuation $v \sim \mathcal{D}_1 \times \cdots \times \mathcal{D}_k$ is drawn from a product distribution, either the best item pricing or the best grand-bundle pricing will earn expected revenue at least $1/6$ times that of an optimal (arbitrarily complex) auction. Babaioff et al. (2014) assume that the D_j's are known a priori and choose item and bundle prices as a function of the distributions. Can we instead learn from samples the best auction from the class consisting of all item and bundle prices? The main result in Babaioff et al. (2014) effectively provides a bound on the representation error of this class; our work provides a bound on the sample complexity and therefore on generalization error (for this and many other classes).

Our Main Results We present a general framework for bounding the sample complexity for "simple" multi-item auctions, when considering auctions as functions from valuations to revenue. Formally, we study the following question, and provide a technique for answering it in many interesting cases:

> Given a class of truthful multiparameter auctions $C : \mathcal{V}^n \to \mathbb{R}$ (each auction maps n-tuples of valuations to the revenue achieved by the auction with those valuations), how large must

1. A canonical "single-parameter" problem is a single-item auction — each bidder either "wins" or "loses". A canonical "multi-parameter" problem is a multi-item auction — with k items, each bidder faces 2^k different possibilities. Multi-parameter problems are well known to be much more ill-behaved than single-parameter problems. For example, there is no general multi-parameter analog of Myerson's (single-parameter) theory of revenue-maximizing auctions (Myerson, 1981).

m be such that the empirical revenue maximizer in C over m independently drawn samples of valuation n-tuples $v^1, \dots, v^m \sim \mathcal{D}$ earns expected revenue at least $OPT(C) - \epsilon$ on fresh sample drawn from $\mathcal{D}$? (Here $OPT(C)$ denotes the maximum expected revenue achieved by an auction in C for the distribution $\mathcal{D}$.)

We note that we have formulated this question as an *unsupervised* learning problem, where the samples given to the learning algorithm are unlabeled. This is the natural model of bidding data from comparable past transactions.

Our main technical contributions are first to show a general way to measure the sample complexity of single-buyer auctions, which are interesting in their own right, and second to show a reduction from bounding the sample complexity for multi-buyer auctions to bounding the sample complexity of single-buyer auctions. Even single-buyer auctions exhibit significant discontinuities in their parameter space which make this endeavor nontrivial. Furthermore, understanding the behavior of a bidder as a function of these parameters is difficult without making assumptions beyond quasilinearity about the structure of their valuation function.

Our framework is flexible enough to bound the sample complexity for most of the simple auction classes that have been studied in the literature. For example, we bound the pseudo-dimension of item pricings, grand bundle pricings, and second-price item or bundle auctions with reserves. The following table summarizes our results, as well as the known approximation guarantees these auctions provide. We note that Theorem 21 is proven using a direct argument rather than our general framework.

Summary of Simple Auction Properties

Class	Valuations	PD anon, nonanon	Rev APX anonymous	Rev APX nonanonymous
Grand bundle pricing	General	$O(1)$, $O(n)$ Corollary 13		
Item Pricing	General	$\tilde{O}(k^2)$, $\tilde{O}(k^2 n)$, Corollary 14	3 (1 unit-demand bidder) (Chawla et al., 2007)	10.7 (n unit-demand bidders) (Chawla et al., 2010)
Item and Grand Bundle Pricing	General	$\tilde{O}(k^2)$, $\tilde{O}(k^2 n)$	6 (1 additive bidder) (Babaioff et al., 2014) 312 (1 subadditive bidder) (Rubinstein and Weinberg, 2015)	
	Additive	$\tilde{O}(k)$, $\tilde{O}(kn)$, Theorem 21		

These results imply that a polynomial-sized sample suffices to learn a nearly-optimal auction from these classes of simple auctions. Equivalently, our results can be thought of as the sample complexity of learning the parameters (e.g., prices) which define each mechanism belonging to one of these classes. Thus, when combined with the "representation error" bounds from the literature, it is possible to learn auctions that earn a constant-factor of the maximum-possible expected revenue for a single additive (Babaioff et al., 2014) or subadditive bidder (Rubinstein and Weinberg, 2015), and n unit-demand bidders (Chawla et al., 2010).[2]

Many of our sample complexity bounds do not rely on any structural assumptions about buyers' valuations — only that their utilities are quasilinear and that they act to maximize their own utility. We point to this flexibility as a key feature of our techniques: for bidders with general valuation functions, it can be quite complicated to reason about bidders' behavior directly. We also formally describe the allocations of these auction classes as coming from *sequential* allocation procedures all drawn from the same class, and show that any class which has allocations which can be described in this way also has a provably simple

2. Our framework also applies to learning simple auctions with good welfare guarantees, as in Feldman et al. (2015); all that changes is the real-valued function associated with an auction. Welfare guarantees are simpler than revenue guarantees (since the objective function value depends on the allocation only) so we concentrate on the latter.

class of allocation functions. This reduction may be of independent interest for proving that other classes of auctions have small sample complexity.

1.1. Related Work

There has been a recent explosion of work on learning near-optimal single-parameter auctions[3] from samples (Elkind, 2007; Balcan et al., 2007, 2008a; Cole and Roughgarden, 2014; Huang et al., 2015; Medina and Mohri, 2014; Roughgarden and Schrijvers, 2015; Morgenstern and Roughgarden, 2015; Devanur et al., 2015); we focus here on the problem of designing auctions from samples for multi-parameter settings. Optimal auctions for combinatorial settings are substantially more complex than for single-parameter settings, even before introducing questions of sample complexity. Dughmi et al. (2014) show that when items' values are allowed to be correlated, for a single unit-demand bidder, the sample complexity required to compute a constant-factor approximation to the optimal auction is necessarily exponential (in m). Sandholm and Likhodedov (2015) consider the computational problem of computing a near-optimal combinatorial auction from samples, but do not address sample complexity.

Item pricings in particular have been the subject of much study with respect to their constant approximations when buyers' values for items are independent, for welfare (Kelso Jr and Crawford, 1982; Feldman et al., 2015) and revenue in the worst-case for a single (Chawla et al., 2007) and n unit-demand bidders (Chawla et al., 2010), a single (Babaioff et al., 2014) additive buyer, and a single subadditive buyer (Rubinstein and Weinberg, 2015).[4] For the additive and subadditive buyer results, the theorems state that the better of the best item pricing and best grand bundle pricing achieve a constant factor of optimal revenue. The n-buyer results for revenue rely on the use of *nonanonymous* item and grand bundle pricings. These results can be thought of as bounding the representation error of using these classes of auctions for revenue maximization; our work can be thought of as complementing these results by bounding the classes' generalization error.

Item pricings are also sufficiently simple that the sample complexity of choosing welfare-optimal (Feldman et al., 2015; Hsu et al., 2016) and revenue-optimal (Balcan et al., 2008a) item pricings has been explored. Balcan et al. (2008a) study the sample complexity of anonymous item pricing for combinatorial auctions with unlimited supply and employ one technique which bears some resemblance to our framework. Fixing a sample of size m, they bound the number of distinct allocation labelings L of that sample by anonymous item pricing using a geometric interpretation of anonymous pricings. Such an argument seems difficult to extend to other classes of auctions (for example, nonanonymous item pricings). We ultimately suggest the use of linear separability as a tool to bound L, an argument which applies to many distinct classes of auctions with finite supply, and doesn't rely on the particular geometry of anonymous item pricings.

We use the concept of linear separability (Crammer and Singer, 2002) to prove bounds on the pseudo-dimension of many classes of auctions; this tool was also used by Balcan et al. (2014) in studying the sample complexity of learning the valuation function of a single buyer when goods are divisible and the valuation functions are either additive, Leontief, or separable and piecewise-linear concave; our results apply to multiple bidders, when items are indivisible, and most of them to arbitrary valuation classes (including superadditive valuations). Hsu et al. (2016) also used linear separability to bound the pseudo-dimension of welfare maximization for item pricings as well as the concentration of demand for any particular good.

3. A generalization of single-item auctions, where each buyer can be described by a single real number representing her value for being selected as a winner.
4. For more general valuation profiles and without item-wise independence, it is known that item pricings can also achieve somewhat weaker revenue approximations, see Balcan et al. (2008b); Chakraborty et al. (2013).

2. Preliminaries

Bayesian Mechanism Design Preliminaries In this section, we provide the definitions and main results regarding simple multi-parameter mechanism design necessary for proving our main results. We consider the problem of selling k heterogeneous items to n bidders. Each bidder $i \in [n]$ can be described by a *combinatorial valuation function* $v_i \in \mathcal{V} \subseteq (2^k \to \mathbb{R})$, and is assumed to be *quasilinear in money*, meaning that her utility for a bundle B with price $p(B)$ is exactly $u_i(B, p) = v_i(B) - p(B)$. We will assume all valuation functions are *monotone*, $v(B) \leq v(B')$ for all $B \subseteq B'$. An auction $\mathcal{A}$ comprises of an allocation rule $\mathcal{A}_1 : \mathcal{V}^n \to [n]^k$ and a payment rule $\mathcal{A}_2 : \mathcal{V}^n \to \mathbb{R}^n$. We will only consider truthful mechanisms, for which it is the best response for any buyer to reveal v_i to the mechanism. The valuation function v_i is assumed to be known to agent i but not to the designer of the auction, who must choose an auction $\mathcal{A}$ before observing $v_1, \ldots, v_n$.

We will assume that bidder i's valuation is drawn independently from some distribution $\mathcal{D}_i$ over valuation profiles. We assume the support of the distribution $\mathcal{D} = \mathcal{D}_1 \times \ldots \times \mathcal{D}_n$ is in $[0, H]^n$. We will refer to the *revenue* of an auction $\mathcal{A}$ on a particular instance $v = (v_1, \ldots, v_n)$ as $\sum_i \mathcal{A}_2(v)_i$, and the (expected) revenue of $\mathcal{A}$ as $\textsc{Rev}(\mathcal{A}, \mathcal{D}) = \mathbb{E}_{v \sim \mathcal{D}}[\sum_i \mathcal{A}_2(v)_i]$. When a bidder's valuation v_i can be represented as $v_{i1}, \ldots, v_{ik}$ such that $v_i(B) = \sum_{j \in B} v_{ij}$, we say that i is *additive*; when v_i can be represented as k numbers $v_{i1}, \ldots, v_{ik}$ such that $v_i(B) = \max_{j \in B} v_{ij}$, we say that i is *unit-demand*. If, for all $B, B' \subseteq [k]$, $v_i(B) + v_i(B') \geq v_i(B \cup B')$, we say v_i is *subadditive*.

Several particular kinds of auctions are of particular use when (approximately) optimizing for revenue in multi-parameter settings. In what follows, when a player chooses a bundle B to maximize her quasilinear utility and B's price is $p_i(B)$, we mean that $\mathcal{A}_1(v)_i = B$ and $\mathcal{A}_2(v)_i = p_i(B)$, i.e., that the allocation and payment rules reflect this choice of B.

An auction is an *item pricing* with ordering σ if it sets price p_{ij} for each $j \in [k], i \in [n]$, and in order $\sigma(1), \ldots, \sigma(n)$ visits buyers, offering to buyer $\sigma(i)$ any bundle $B \subseteq [k] \setminus \cup_{\sigma(i'):i'<i} B_{i'}$ at price $\sum_{j \in B} p_{\sigma(i)j}$, and buyer $\sigma(i)$ purchases a quasilinear utility-maximizing bundle $B_{\sigma(i)} \in \operatorname{argmax}_{B \subseteq [m] \setminus \cup_{\sigma(i'):i'<i} B_{i'}} v_i(B) - \sum_{j \in B} p_{\sigma(i)j}$. A *grand bundle pricing* with order σ sets a single price p_i for the "grand" bundle $[k]$ of all items, and visits buyers in order $\sigma(1), \ldots, \sigma(n)$, offering to buyer $\sigma(i)$ the bundle $[k]$ for price p_i if no other $\sigma(i') : i' < i$ purchased $[k]$, and $\sigma(i)$ purchases $[k]$ if and only if $v_i([k]) \geq p_i$. If these prices do not depend on the identity of the bidders (i.e. $p_{ij} = p_{i'j}$ for all i, i', j, or $p_i = p_{i'}$ for all i, i'), we say these prices are *anonymous*, otherwise that they are *nonanonymous* pricings. Throughout the paper, we will assume some σ is fixed (namely, not a parameter of the design space), and so we rename bidders according to their location in this fixed ordering. When buyers are additive, we will consider two types of auctions. First, we consider the *second-price* item auction, which sells each item to the highest bidder for that item at the second-highest bid for that item. Finally, we will consider the second-price item (grand-bundle) auction with both anonymous and non-anonymous item reserves, which sell to the highest bidder for that item at the maximum of the second-highest bid and the item's reserve (for that bidder), or to no one if the highest bidder's bid is below her reserve. These auction classes achieve constant-factor approximations for revenue in many special cases: for one (Chawla et al., 2007) and n (Chawla et al., 2010) unit-demand bidders, for one additive (Babaioff et al., 2014) and one subadditive bidder (Rubinstein and Weinberg, 2015) (see Section C, where we have included the formal theorem statements for completeness). In the full version of this paper, we consider an additional class of auctions necessary to achieve a constant factor approximation for n additive bidders as in Yao (2015). In all of these cases, we consider some *class* of auctions (e.g., item pricings, grand bundle pricings, VCG with (second-price) reserves, or entrance mechanisms), and bound the sample complexity of each class, which analogously can be thought of as the sample complexity of learning the parameters (e.g., prices) which define each mechanism.

Learning Theory Preliminaries In this section, we provide definitions and useful tools for bounding the sample complexity of learning real-valued functions. We omit discussion of binary-labeled learning and the definitions of uniform versus PAC learning for reasons of space (see Section B for further details).

Real-Valued Labels In order to learn real-valued functions (for example, to guarantee convergence of the revenue of various auctions), we use a real-valued analog of VC dimension. This gives a sufficient but not always necessary condition for uniform convergence. We will work with the *pseudo-dimension* (Pollard, 1984), one standard generalization. Formally, let $c : \mathcal{V} \to [0, H]$ be a real-valued function over $\mathcal{V}$, and $\mathcal{F}$ be the class of functions that we are learning over. Let S be a sample drawn from $\mathcal{D}$, $|N| = m$, labeled according to c. Let $\text{err}_N(\hat{c}) = (\sum_{v \in N} |c(v) - \hat{c}(v)|)/|N|$ denote the empirical error of $\hat{c}$ on N, and let $\text{err}(\hat{c}) = \mathbb{E}_{v \sim \mathcal{D}}[|c(v) - \hat{c}(v)|]$ denote the *true* expected error of $\hat{c}$ with respect to $\mathcal{D}$. Let $(r_1, \ldots, r_m) \in [0, H]^m$ be a set of *targets* for N. We say $(r_1, \ldots, r_m)$ *witnesses* the shattering of N by $\mathcal{F}$ if, for each $T \subseteq N$, there exists some $c_T \in \mathcal{F}$ such that $c_T(v_q) \geq r_q$ for all $v_q \in T$ and $c_T(v_q) < r_q$ for all $v_q \notin T$. If there exists some $\boldsymbol{r}$ witnessing the shattering of N, we say N is *shatterable* by $\mathcal{F}$. The *pseudo-dimension* of $\mathcal{F}$, denoted $\mathcal{PD}(\mathcal{F})$, is the size of the largest set S which is shatterable by $\mathcal{F}$. We will derive sample complexity upper bounds from the following theorem, which connects the sample complexity of uniform learning over a class of real-valued functions to the pseudo-dimension of the class.

Theorem 1 (E.g. Anthony and Bartlett (1999)) *Suppose $\mathcal{F}$ is a class of real-valued functions with range in $[0, H]$ and pseudo-dimension $\mathcal{PD}(\mathcal{F})$. For every $\epsilon > 0, \delta \in [0, 1]$, the sample complexity of (ϵ, δ)-uniformly learning the class $\mathcal{F}$ is*

$$n = O\left(\left(\frac{H}{\epsilon}\right)^2 \left(\mathcal{PD}(\mathcal{F}) \ln \frac{H}{\epsilon} + \ln \frac{1}{\delta}\right)\right).$$

Theorem 1 suggests a simple learning algorithm: simply output the function $c \in \mathcal{F}$ with the largest empirical revenue on the sample. We call such algorithms *empirical revenue maximizers*.

Multiclass Learning The main goal of our work is to bound the sample complexity of revenue maximization for multi-parameter classes of auctions (via bounding these classes' pseudo-dimension); our proofs first bound the number of labelings of *purchased bundles* which these auctions can induce on a sample of size m. Then, we argue about the behavior of the revenue of all auctions which agree on the purchased bundles for every sample to bound the pseudo-dimension. Since bundles are neither binary nor real-valued, we now briefly mention several tools which we use for learning in the so-called *multi-label* setting.

The first of these tools is that of *compression schemes* for a class of functions.

Definition 2 *A* compression scheme *for $\mathcal{F} : \mathcal{V} \to \mathcal{Y}$, of size d consists of*

- *a* compression *function*
$$\textbf{\textit{compress}} : (\mathcal{V} \times \mathcal{Y})^m \to (\mathcal{V} \times \mathcal{Y})^d,$$
where $\textbf{\textit{compress}}(N) \subseteq N$ *and* $d \leq m$*; and*
- *a* decompression *function*
$$\textbf{\textit{decompress}} : (\mathcal{V} \times \mathcal{Y})^d \to \mathcal{F}.$$

For any $f \in \mathcal{F}$ and any sample $(v_1, f(v_1)), \ldots, (v_m, f(v_m))$, the functions satisfy

$$\textbf{\textit{decompress}} \circ \textbf{\textit{compress}}((v_1, f(v_1)), \ldots, (v_m, f(v_m))) = f' \in \mathcal{F}$$

where $f'(v_q) = f(v_q)$ for each $q \in [m]$.

Intuitively, a compression function selects a subset of d "most relevant" points from a sample, and based on these points, the decompression scheme selects a hypothesis. When such a scheme exists, the learning algorithm **decompress** $\circ$ **compress** is an empirical risk minimizer. Furthermore, this compression-based learning algorithm has sample complexity bounded by a function of d, which plays a role analogous to VC dimension in the sample complexity guarantees.

Theorem 3 (Littlestone and Warmuth (1986)) *Suppose $\mathcal{F}$ has a compression scheme of size d. Then, the* PAC *sample complexity of $\mathcal{F}$ is at most $m = O\left(\frac{d \ln \frac{1}{\epsilon} + \ln \frac{1}{\delta}}{\epsilon}\right)$.*

While compression schemes imply useful sample complexity bounds, it can be hard to show that a particular hypothesis class admits a compression scheme. One general technique is to show that the class is linearly separable in a higher-dimensional space.

Definition 4 *A class $\mathcal{F}$ is d-*dimensionally linearly separable *over labels $\mathcal{Y}$ if there exists a function $\psi : \mathcal{V} \times \mathcal{Y} \to \mathbb{R}^d$ and for any $f \in \mathcal{F}$, there exists some $w^f \in \mathbb{R}^d$ with $f(v) \in argmax_y \langle w^f, \psi(v, y)\rangle$ and $|argmax_y \langle w^f, \psi(v, y)\rangle| = 1$.*

It is known that a d-dimensional linearly separable class admits a compression scheme of size d.

Theorem 5 (Theorem 5 of Daniely and Shalev-Shwartz (2014)) *Suppose $\mathcal{F}$ is d-dimensionally linearly separable. Then, there exists a compression scheme for $\mathcal{F}$ of size d.*

If a class is linearly separable, this greatly restricts the number of labelings it can induce on a sample of size m, a trick used in Hsu et al. (2016) and also in the next section of this paper.

We also briefly mention that if a class $\mathcal{F}$ is linearly separable, then post-processing the class with a fixed function also yields a compression scheme over the resulting label space.

Observation 1 *Suppose $\mathcal{F}$ is d-dimensionally linearly separable over $\mathcal{Y}$. Fix some $q : \mathcal{Y} \to \mathcal{Y}'$. Then, there exists a compression scheme for $q \circ \mathcal{F} = \{q \circ f | f \in \mathcal{F}\}$ of size d over $\mathcal{Y}'$.*

With these tools in hand, our roadmap is as follows: for a class of auctions, we first prove that the class (which labels valuations by utility-maximizing bundles purchased) is linearly separable, which then implies an upper bound on how many distinct bundle labelings one can have for a fixed sample. Then, we argue about the pseudo-dimension of the class (which labels a valuation by the revenue achieved when that agent buys her utility-maximizing bundle) by considering only those auctions which all have the same bundle labeling of m samples and arguing about the behavior of the revenue of those auctions.

3. A Framework for Bounding Pseudo-dimension Via Intermediate Discrete Labels

We now propose a new framework for bounding the pseudo-dimension of many well-structured classes of real-valued functions. Suppose $\mathcal{F}$ is some set of real-valued functions whose pseudo-dimension we wish to bound. Suppose that, for each $f \in \mathcal{F}$, f can be "factored" into a pair of functions (f_1, f_2) such that $f_2(f_1(x), x) = f(x)$ for any x. There are always "trivial" factorings, where the function $f_2 = f$ or $f_1(x) = x$, but the interesting case arises when both $f_1(x)$ and f_2 (fixing $f_1(x)$) depend in a very limited way upon x. In particular, if the set of functions $\{f_1\}$ are very structured, and fixing $f_1(x)$ the set of functions $\{f_2\}$ only depend upon x in some very mild way, this will imply that $\mathcal{F}$ itself has small pseudo-dimension.

Intuitively, this will allow us to "bucket" functions by their values according to f_1 on some sample, and bound the pseudo-dimension of each of those buckets separately.

Our particular technique for showing such a property is first to show that the set of functions $\{f_1\}$ are *linearly separable* in a dimensions, then to fix some sample S of size m and some f_1, and to upper-bound by b the pseudo-dimension of the set of functions f_2 whose associated f_1' agrees with the labeling of f_1 on S. The following definition captures precisely what we mean when we say that the function class $\mathcal{F}$ *factors* into these two other classes of functions. If $f_1(x)$ reveals too much about x, it will be difficult to prove linear separability; similarly, if f_2 depends too heavily on x, it will be difficult to prove a bucket has small pseudo-dimension.

Definition 6 ((a, b)-factorable class over Q) Consider some $\mathcal{F} = \{f : \mathcal{X} \to \mathbb{R}\}$. Define for each $f \in \mathcal{F}$ a decomposition, in the form of two functions $f_1 : \mathcal{X} \to \mathcal{Y}$ and $f_2 : \mathcal{Y} \times \mathcal{X} \to \mathbb{R}$ such that $f_2(f_1(x), x) = f(x)$ for every $x \in \mathcal{X}$. Let

$$\mathcal{F}_1 = \{f_1 : (f_1, f_2) \text{ is a decomposition of some } f \in \mathcal{F}\}$$

and

$$\mathcal{F}_2 = \{f_2 : (f_1, f_2) \text{ is a decomposition of some } f \in \mathcal{F}\}.$$

The set $\mathcal{F}$ (a, b)*-factors over* Q if:

(1) $\mathcal{F}_1$ is a-dimensionally linearly separable over $Q \subseteq \mathcal{Y}$.

(2) For every $f_1 \in \mathcal{F}_1$ and sample $S \subset \mathcal{X}$, the set

$$\begin{aligned}\mathcal{F}_{2|f_1(S)} = \{f_2' : S \to \mathbb{R}, f_2'(x) = f_2(f_1'(x), x) | f_1(x) = f_1'(x) \forall x \in S \\ \text{and } (f_1', f_2) \text{ is a decomposition of some } f \in \mathcal{F}\}\end{aligned}$$

has pseudo-dimension at most b.

We now give an example of a simple class which satisfies this definition. One could easily bound the pseudo-dimension of this example class using a direct shattering argument, but it will be instructive to work through our definition of (a, b)-separability.

Example 1 Fix some set $G = \{g_1, \ldots, g_k\} \subset \mathbb{R}^k$. Suppose $\mathcal{F} = \{f : f(x) = \max_{g \in G_f \subseteq G} g \cdot x\}$ is the set of all functions which take the maximum of at most k common linear functions in a fixed set G. We will show that $\mathcal{F}$ $(kd, \tilde{O}(kd))$-factors over $[k]$, where each $j \in [k]$ will represent *which* of the k linear functions is maximizing for a particular input. That is, for some $f, G_f \subseteq G$, let $f_1(x) = \text{argmax}_{t: g_t \in G_f} g_t \cdot x$ and $f_2(t, x) = g_t \cdot x$. Thus, we have a valid factoring:

$$f_2(f_1(x), x) = f_2(\text{argmax}_{t: g_t \in G_f} g_t \cdot x, x) = g_{\text{argmax}_{t: g_t \in G_f} g_t \cdot x} \cdot x = \max_{g_t \in G_f} g_t \cdot x = f(x).$$

It remains to show that $\mathcal{F}_1$ is d-dimensionally linearly separable and to bound the pseudo-dimension of $\mathcal{F}_{2|f_1}$. We start with the former. Let $\Psi(x, t)_{t'j} = \mathbb{I}[t' = t] \cdot x_j$ for $t' \in [k], j \in [d]$. Then, let $w^f_{tj} = \mathbb{I}[g_t \in G_f] \cdot g_{tj}$. The dot product will then be

$$\Psi(x, t) \cdot w^f = \sum_{t'} \mathbb{I}[t' = t] \cdot \mathbb{I}[g_{t'} \in G_f] g_{t'} \cdot x$$

which will be maximized when $t = \text{argmax}_{t':g_{t'} \in G_f} g_{t'} \cdot x$, or when $t = f_1(x)$. So, $\mathcal{F}_1$ is linearly separable in kd dimensions over $[k]$.

Now, fix $f_1 \in \mathcal{F}_1$; we will show the pseudo-dimension of $\mathcal{F}_{2|f_1}$ is at most $\tilde{O}(kd)$. For any fixed sample $S = (x^1, \ldots, x^m)$, $f_1(x^t)$ is fixed for all $t \in [m]$, implying that the input to all $f_2 \in \mathcal{F}_{2|f_1}$, $(f_1(x^t), x^t)$, is fixed. Finally, by definition of f_2',

$$f_2'(x^t) = f_2(f_1(x^t), x^t) = g_{f_1(x^t)} \cdot x^t.$$

Thus, for each $j \in [k]$, the subset $S_j \subseteq S$ for which $f_1(x^t) = j$ for all $x^t \in S_j$, f_2' is just a linear function in d dimensions of x^t with coefficients g_j, Thus, since linear functions in d dimensions have pseudo-dimension at most $d+1$, there are at most m^{d+1} labelings which can be induced on S_j, and at most $m^{k(d+1)}$ labelings of all of S. This implies $\mathcal{PD}(\mathcal{F}_{2|f_1})$ is at most $\tilde{O}(kd)$.

We now present the main theorem about the pseudo-dimension of classes that are (a, b)-factorable. The proof of this theorem first exploits the fact that linearly separable classes have a "small" number of possible outputs for a sample of size m. Then, fixing the output of the linearly separable function, the second set of functions' pseudo-dimension is small. The proof of the theorem is relegated to the appendix due to space considerations.

Theorem 7 *Suppose $\mathcal{F}$ is (a, b)-factorable over Q. Then,*

$$\mathcal{PD}(\mathcal{F}) = O\left(\max\left((a+b)\ln(a+b), a\ln|Q|\right)\right).$$

Intuitively, when $\mathcal{F}_1$ is linearly separable in a dimensions, it can induce at most $m^a|Q|^a$ many labelings of m samples, and fixing such a sample and its labeling, because $\mathcal{F}_2$ has pseudo-dimension at most b, it can induce at most m^b labelings of m samples with respect to their thresholds.

While the range of $\mathcal{F}_1$ might be all of Q, it will regularly be helpful to only need to prove linear separability of $\mathcal{F}_1$ only over "realizable" labels for particular inputs. If $\mathcal{F}_1$ has the property that for every input x, every $f_1 \in \mathcal{F}_1$ labels x with one of a smaller set of labels $Q_x \subsetneq Q$, then it suffices to prove linear separability *for* x over Q_x.[5] The following remark makes this claim formal; its proof can be found in Section E. So, we will be able to focus on proving linear separability of $\mathcal{F}_1$ over a label space which depends upon the inputs x. This will be particularly useful when describing auctions in the next section, whose allocations are in certain cases highly restricted by their inputs. For example, when considering auctions which only ever sell item j to the highest bidder for j, while any possible allocation might occur, we can restrict our attention to those allocations for a sample which only allocate j too the highest bidder for j.

Remark 8 *Suppose for each $x \in \mathcal{X}$, there exists some $Q_x \subseteq Q$ such that $f_1(x) \in Q_x \subseteq Q$ for all $f_1 \in \mathcal{F}_1$, and that for each x, $\mathcal{F}_1$ is linearly separable in a dimensions for that x over Q_x. Assume there is a subset of dimension $T^+ \subseteq [a]$ for which $w^f_{t \in T^+} \geq 0$ and $\sum_{t \in T^+} w^f_t > 0$ for all f. Suppose that for all $x \in X, f \in \mathcal{F}_1$, $\max_{y \in Q_x} \Psi(x, y) \cdot w^f \geq 0$. Then, $\mathcal{F}_1$ is linearly separable over Q in a dimensions as well.*

We also briefly mention a version of Theorem 7 holds if F_1 needs to be *post-processed*. If F has a decomposition into some $g \circ \mathcal{F}_1, F_2$, for some fixed, known $g : Q \to Q'$, and $\mathcal{F}_1$ is a-dimensionally linearly separable over Q and $F_{2|f_1(S)}$ has pseudo-d imension at most b, we will say that $\mathcal{F}$ (a, b, g)-factors over the label space Q'.

Remark 9 *Suppose $\mathcal{F}$ (a, b, g)-factors over the label space Q'. Then*

$$\mathcal{PD}(\mathcal{F}) = O\left(\max\left((a+b)\ln(a+b), a\ln|Q'|\right)\right).$$

5. The function-specific weight vectors w^f should be defined independently of x, as usual.

4. Consequences for Learning Simple Auctions

4.1. Overview

We now present applications of the framework provided by Theorem 7 to prove bounds on the pseudo-dimension for many classes of "simple" multi-item auctions. The implication is that these classes, which have been shown in many special cases to have small representation error, also have small generalization error when auctions are chosen after observing a polynomially sized sample. We now describe how one can translate a class of auctions into a class of functions which has an obvious and useful factorization. An auction $\mathcal{A} : \mathcal{V}^n \to [n]^k \times [0, H]^n$ has two components, its *allocation function* $\mathcal{A}_1 : \mathcal{V}^n \to [n]^k$ and its *revenue function* $\mathcal{A}_2 : \mathcal{V}^n \to [0, H]^n$. We will abuse notation and refer to $\mathcal{A}_2(\mathbf{v}) = \sum_i A(\mathbf{v})_{2i}$ as the revenue function for an auction. Our goal is to bound the sample complexity of picking some high-revenue function from a class. All omitted proofs are found in Section E. For the remainder of this section we use $\mathcal{F}$ to represent a class of auctions, $f \in \mathcal{F}$ to represent a particular auction, and $\mathcal{F}_1, \mathcal{F}_2$ to be the corresponding allocation functions and revenue functions which result from this decomposition. When $\mathcal{F}_1$ is linearly separable, this implies there can only be so many distinct allocations possible for a fixed set of valuation profiles S, and when $\mathcal{F}_2$ (fixing some allocation for S) has small pseudo-dimension, the class of auctions itself has small pseudo-dimension. We assume for the remainder of the paper that there are no ties, (that is, there are no menus or bidders for which $|\text{argmax}_B u(B)| > 1$).[6]

This "trivial" decomposition of an auction's revenue function describes its revenue function as a function of both the allocation chosen by $f_1 \in \mathcal{F}_1$ for $\mathbf{v}$ and the valuation profile $\mathbf{v}$. Since A_2 is a function only of $\mathbf{v}$, there is clearly enough information in $(f_1(\mathbf{v}), \mathbf{v})$ to compute $\mathcal{A}_2(\mathbf{v})$ (one can simply ignore $f_1(\mathbf{v})$ and output $f_2(f_1(\mathbf{v}), \mathbf{v}) = \mathcal{A}_2(\mathbf{v})$). The reason we consider this decomposition is that fixing an allocation, revenue functions of simple auctions are generally very simple to describe as a function of the input valuation profile $\mathbf{v}$. If one fixes the allocation choice for a sample S of m valuations, many auctions' classes of revenue functions are either constant functions on S which do not depend upon $\mathbf{v}$ at all (for example, a posted price auction for a single item offered to a single bidder earns its posted price if the item sells and 0 when the item doesn't sell, both of which are constants when the allocation is fixed) or depends only in a very mild way (for example, a second-price single-item auction with a reserve earns the maximum of its reserve and the second-highest bid when the item sells and 0 when it doesn't).

4.2. Item Prices for a Single Buyer

For our first example, we employ our framework to show that single-buyer item pricings have small pseudodimension, regardless of the buyer's valuation type (e.g., additive, unit-demand, submodular, subadditive, or arbitrary).

Theorem 10 *Let $\mathcal{F}$ represent the class of item pricings for a single buyer and k goods. Then, $\mathcal{PD}(\mathcal{F}_2) \leq O(k^2 \ln(k))$.*

Proof We will first show $\mathcal{F}_1$ is $k+1$-dimensionally linearly separable with respect to the label set $\{B : B \subseteq \{1, 2, \ldots, k\}\}$, and then that $\mathcal{F}_{2|f_1(S)}$ has pseudo-dimension $O(k)$. Then, Theorem 7 will imply the pseudodimension bound.

We start by showing $\mathcal{F}_1$ is $k+1$-dimensionally linearly separable. Let

$$\Psi(v, B) = (v(B), \mathbb{I}[1 \in B], \ldots, \mathbb{I}[k \in B])$$

6. We elide further discussion on this technical point, though we note it is possible to encode a tie-breaking rule over utility-maximizing bundles in a way which is linearly separable (see Hsu et al. (2016) for more details).

and

$$w^{f_1^p} = (1, -p_1, \ldots, -p_k)$$

for any item pricing $f_1^p \in \mathcal{F}_1, p \in \mathbb{R}^k$. Then, the dot product

$$\langle \Psi(v, B), w^{f_1^p} \rangle = v(B) - \sum_{i \in B} p_i = u(B)$$

encodes a quasilinear buyer's utility for a bundle B; thus, the bundle label which maximizes this dot product is the bundle that maximizes the buyer's utility. Since a buyer acts to maximize her quasilinear utility, $f_1^p(v) = B = \text{argmax}_{B'} \langle \Psi(v, B'), w^{f_1^p} \rangle$, as desired.

Finally, we show that $\mathcal{F}_{2|f_1(S)}$ has pseudo-dimension $O(k)$. For $S = (v^1, \ldots, v^m)$, $f_2^p(f_1^p(v^t), v^t) = \sum_{i \in f_1^p(v^t)} p_i$: revenue is simply a linear function of the k prices of the auction. Since k-dimensional linear functions have pseudo-dimension at most $O(k)$, this proves the claim. ■

4.3. Multiple-Buyer Mechanisms

We now show that our framework is general enough to handle mechanisms with multiple buyers. Most of the "simple" auctions with multiple buyers and items that have been considered are *anonymous or nonanonymous auctions* which interact with buyers "one at a time": first, bidder 1 is offered a "menu" of several possible allocations at different prices, and she chooses some bundle; then bidder 2 is offered one of several allocations of the remaining items at different prices, and so on. (Of course, any auction in a single-buyer scenario is trivially of this form.) These auctions are simple enough that they can actually be run in practice, and yet expressive enough that in many cases can earn a constant fraction of the optimal revenue.

We next work toward a general reduction, from bounding the sample complexity of nonanonymous auctions (with multiple buyers) to that of single-buyer auctions. The following definition captures two particularly common forms of these auctions. The first definition captures the setting where the function selecting the menu to bidder i may depend upon i's identity; the second refers to when the menu is *anonymous*: what may be offered to bidder i can be different than what is offered to bidder i', but only due to the differences in bids $v_i, v_{i'}$ and the remaining available items $X_i(v), X_{i'}(v)$.

For example, consider a single item for sale. Suppose n buyers are approached in some fixed order and bidder i is offered the item at price p_i if no earlier buyer has purchased the item. If $p_i = p_{i'}$ for all $i, i' \in [n]$, then the auction applied to each buyer is the same, and we say this auction applies an n-wise repeated allocation associated with a single posted price. If $p_i \neq p_{i'}$ for some $i, i' \in [n]$, then the allocation function applied to each bidder is an allocation rule associated with some single posted price, though the particular posted price and therefore the allocation function varies from bidder to bidder; this auction's allocation is therefore an n-wise sequential allocation drawn from the class of posted prices.

For a slightly more complex example, consider a set of k heterogeneous items $[k]$ for sale to n bidders. Consider an auction which sets a price p_{ij} for each item $j \in [k]$ and each bidder $i \in [n]$, and serves bidders in some fixed order. Bidder i is offered any bundle B for which no item has been selected by some previous bidder at price $p_i(B) = \sum_{j \in B} p_{ij}$. This allocation is reached by applying a posted item pricing allocation to each buyer in turn, so these allocations are n-wise sequential allocations drawn from posted item pricing allocations. If $p_{ij} = p_{i'j}$ for all $j \in [k]$ and all $i, i' \in [n]$, then the same allocation rule is being applied to all bidders, and the overall allocation is therefore an n-wise repeated allocation rule.

Definition 11 (n-wise repeated and sequential allocations) *Let $\mathcal{H}$ be some class with $h : \mathcal{V} \times \{0,1\}^k \to Q$ for all $h \in \mathcal{H}$ and some $Q \subseteq \{0,1\}^k$. For some n functions $h_1, \ldots, h_n \in \mathcal{H}$ and every $\mathbf{v} \in \mathcal{V}^n$,* *inductively define* $X_1(\mathbf{v}) = [k], X_i(\mathbf{v}) = X_{i-1}(\mathbf{v}) \setminus h_{i-1}(\mathbf{v}_{i-1}, X_{i-1}(\mathbf{v}))$. *Then, define the* n*-wise product function* $\prod_{(h_1,\ldots,h_n)}$ *to be*

$$\prod_{(h_1,\ldots,h_n)}(\mathbf{v}) = (h_1(\mathbf{v}_1, X_1(\mathbf{v})), h_2(\mathbf{v}_2, X_2(\mathbf{v})), \ldots h_n(\mathbf{v}_n, X_n(\mathbf{v}))).$$

Then, we call any such function an n*-wise* sequential allocation drawn from $\mathcal{H}$. *If* $h_1 = h_2 = \ldots = h_n$, *we call* $\prod_{h_1,\ldots,h_n}$ *an* n*-wise repeated allocation drawn from* $\mathcal{H}$.

The sets $X_1, \ldots, X_n$ correspond to the sets of remaining available items for each bidder after the previous bidders have purchased their bundles according to their allocation functions: what is remaining for bidder i is whatever bidder $i-1$ had available less whatever was allocated to bidder $i-1$. The two previous examples fit into this scenario perfectly. The per-bidder allocation functions are fixed up-front: the allocation rules brought about by an (anonymous) price for a single item or (anonymous) prices for each item. In some fixed order, the bidders are allocated according to their allocation rule run on their valuation and the remaining items, and whatever items they didn't purchase are available for the next bidder and her allocation rule. When the prices don't depend on the index i, the allocation function for each bidder is the same, so those cases correspond to n-wise repeated allocation rules, which are a subset of the n-wise sequential allocation rules which might apply a different allocation rule to each bidder.

In the event that some class of auctions' allocation functions $\mathcal{F}_1$ are made up of n-wise sequential allocations from a class $\mathcal{H}$ which is linearly separable, the linear separability is imparted upon $\mathcal{F}_1$. This intuition is made formal by the following theorem.

Theorem 12 *Suppose* $\mathcal{F}$ *is a class of auctions, and let* $\mathcal{F}_1 : \mathcal{V}^n \to Q \subseteq [n]^k$ *be their (feasible) allocation function. Suppose* $\mathcal{F}_1$ *is a set of* n*-wise sequential allocations from some* $\mathcal{H}$ *which is* a*-dimensionally linearly separable, whose dot products are upper-bounded by* H. *Then* $\mathcal{F}_1$ *is* an*-dimensionally linearly separable. Similarly, if* $\mathcal{F}_1$ *is a set of* n*-wise repeated allocations drawn from* $\mathcal{H}$ *which is* a*-dimensionally linearly separable, then* $\mathcal{F}_1$ *is also* a*-dimensionally linearly separable.*

Roughly speaking, this proof takes the maps guaranteed by linear separability of $\mathcal{H}$ and concatenates them n times, "blowing up" the relative importance of the earlier bidders with large coefficients.

We now present the three main corollaries of Theorems 7 and 12 which bound the pseudo-dimension of several auction classes of interest to the mechanism design community. In particular, we focus on "grand bundle" pricings (Corollary 13), where each bidder in turn is offered the entire set of items $[k]$ at some price, and "item pricings" (Corollary 14), where each bidder in turn is offered all remaining items and each item j has some price for purchasing it. Both of these auctions have two versions: the anonymous version, where the relevant design parameters are the same for all bidders, and the non-anonymous version, where those parameters can be bidder-specific. As one would suspect, anonymous pricings have fewer degrees of freedom, and have lower pseudo-dimension. More formally, the allocations which come from anonymous pricings can be formulated as n-wise anonymous allocations, while we formulate non-anonymous pricings' allocations as n-wise sequential allocations (which, by Theorem 12 loses a factor of n in the upper bound on these classes' pseudo-dimensions). In each case, $\mathcal{F}_1$ will represent allocation functions: $f_1 \in \mathcal{F}_1$ corresponds to the allocation function which the auction will implement for quasilinear bidders. For every class $\mathcal{F}$, we define for every auction $f \in \mathcal{F}$ the function f_2 to be the *revenue* function, which as a function of an allocation and the valuation profile outputs the revenue for that auction with that allocation for that valuation profile. The decomposition of $\mathcal{F}$ into $\mathcal{F}_1, \mathcal{F}_2$ is trivial; the work comes in showing that $\mathcal{F}_1$ is linearly separable and $\mathcal{F}_{2|f_1}$ has small pseudo-dimensions.

Our first two results use the framework to that grand bundle pricings and item pricings have small pseudo-dimension. The second case requires a more delicate treatment of the valuation profiles (buyers are now choosing arbitrary subsets of items, and will choose utility-maximizing bundles based on the per-item prices). It also requires us to consider a larger set of intermediate labels (the set of all possible allocations grows to $[n]^k$ from $[n]$).

Corollary 13 *Let $\mathcal{F}$ be the class of anonymous grand bundle pricings. Then,*

$$\mathcal{PD}(\mathcal{F}) = O(1).$$

If $\mathcal{F}$ is the class of non-anonymous grand bundle pricings, then

$$\mathcal{PD}(\mathcal{F}) = O(n \log n).$$

Corollary 14 *Let $\mathcal{F}$ be the class of anonymous item pricings. Then,*

$$\mathcal{PD}(\mathcal{F}) = O\left(k^2\right).$$

If $\mathcal{F}$ is the class of nonanonymous item pricings, then

$$\mathcal{PD}(\mathcal{F}) = O\left(nk^2 \ln(n)\right).$$

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Appendix A. Open Problems

We propose the following open problems resulting from our work.

1. Is it possible to construct "compression-style" arguments which bound the pseudo-dimension of the revenue of the class of item pricings for additive bidders which are tight (giving a bound of k and nk, as in Theorem 21, rather than k^2 and nk^2)?

2. For general or even subadditive valuations, do item pricings have pseudo-dimension $O(nk)$ or strictly larger?

3. Is it possible to frame the allocations which result from item pricings with item-specific reserves as n-fold sequential allocation rules from some simple class, for general valuation functions? We were able to show it for additive valuations, which allowed us to use the "trick" where the highest bidder for an item is willing to pay anything less than her bid for that item (independent of other prices); thus, if she's willing to pay the reserve, by virtue of being the highest bidder for the item she's willing to pay the second-highest bid as well. For more general valuations, she may or may not optimize her utility by paying some combination of item prices and second-highest bids for a bundle which was utility-optimal if she were only paying item prices.

4. Relatedly, what is the pseudo-dimension of second-price item auctions with item-specific reserves when bidders have valuations which are more general than additive or unit-demand? One can use a proof similar to the proof of Theorem 21 to achieve a bound for unit-demand bidders, but what about for submodular or subadditive bidders? It isn't clear that the relative ordering of a small number of "relevant" parameters (such as per-item price and per-bidder single-item values) of the auction and sample are sufficient to fix the most-preferred bundle for each agent from a sample.

Appendix B. Binary Labeled Learning

Suppose there is some domain $\mathcal{V}$, and let c be some unknown target function $c : \mathcal{V} \to \{0, 1\}$, and some unknown distribution $\mathcal{D}$ over $\mathcal{V}$. We wish to understand how many labeled samples $(v, c(v))$, with $v \sim \mathcal{D}$, are necessary and sufficient to be able to compute a $\hat{c}$ which agrees with c almost everywhere with respect to $\mathcal{D}$. The distribution-independent sample complexity of learning c depends fundamentally on the "complexity" of the set of binary functions $\mathcal{F}$ from which we are choosing $\hat{c}$. We review two standard complexity measures next.

Let N be a set of m samples from $\mathcal{V}$. The set N is said to be *shattered* by $\mathcal{F}$ if, for every subset $T \subseteq N$, there is some $c_T \in \mathcal{F}$ such that $c_T(v) = 1$ if $v \in T$ and $c_T(v') = 0$ if $v' \notin T$. That is, ranging over all $c \in \mathcal{F}$ induces all $2^{|N|}$ possible projections onto N. The *VC dimension* of $\mathcal{F}$, denoted $\mathcal{VC}(\mathcal{F})$, is the size of the largest set S that can be shattered by $\mathcal{F}$.

Let $\text{err}_N(\hat{c}) = (\sum_{v \in N} |c(v) - \hat{c}(v)|)/|N|$ denote the empirical error of $\hat{c}$ on N, and let $\text{err}(\hat{c}) = \mathbb{E}_{v \sim \mathcal{D}}[|c(v) - \hat{c}(v)|]$ denote the *true* expected error of $\hat{c}$ with respect to $\mathcal{D}$. We say $\mathcal{F}$ is (ϵ, δ)-PAC *learnable with sample complexity* m if there exists an algorithm $\mathcal{A}$ such that, for all distributions $\mathcal{D}$ and all target functions $c \in \mathcal{F}$, when $\mathcal{A}$ is given a sample S of size m, it produces some $\hat{c} \in \mathcal{F}$ such that $\text{err}(\hat{c}) < \epsilon$, with probability $1-\delta$ over the choice of the sample. The PAC sample complexity of a class $\mathcal{F}$ can be bounded as a polynomial function of $\mathcal{VC}(\mathcal{F})$, ϵ, and $\ln \frac{1}{\delta}$ (Vapnik and Chervonenkis, 1971); furthermore, any algorithm which (ϵ, δ)-PAC learns $\mathcal{F}$ over all distributions $\mathcal{D}$ *must* use nearly as many samples to do so. The following theorem states this well-known result formally.[7]

Theorem 15 (Upper bound (Hanneke, 2015), Lower bound, Corollary 5 of (Ehrenfeucht et al., 1989)) *Suppose $\mathcal{F}$ is a class of binary functions. Then, $\mathcal{F}$ can be (ϵ, δ)-PAC learned with a sample of size*

$$m = O\left(\frac{\mathcal{VC}(\mathcal{F}) + \ln \frac{1}{\delta}}{\epsilon}\right).$$

*Furthermore, any (ϵ, δ)-*PAC *learning algorithm for $\mathcal{F}$ must have sample complexity*

$$m = \Omega\left(\frac{\mathcal{VC}(\mathcal{F}) + \ln \frac{1}{\delta}}{\epsilon}\right).$$

There is a stronger sense in which a class $\mathcal{F}$ can be learned, called *uniform learnability*. This property implies that, with a sufficiently large sample, the error of *every* $c \in \mathcal{F}$ on the sample is close to the true error of c. We say $\mathcal{F}$ is (ϵ, δ)*-uniformly learnable with sample complexity* m if, for every distributions $\mathcal{D}$, given a sample N of size m, with probability $1-\delta$, $|\text{err}_N(c) - \text{err}(c)| < \epsilon$ for every $c \in \mathcal{F}$. Notice that, if $\mathcal{F}$ is (ϵ, δ)-uniformly learnable with m samples, then it is also (ϵ, δ)-PAC learnable with m samples. We now state a well-known upper bound on the uniform sample complexity of a class as a function of its VC dimension.

Theorem 16 (See, e.g. Vapnik and Chervonenkis (1971)) *Suppose $\mathcal{F}$ is a class of binary functions. Then, $\mathcal{F}$ can be (ϵ, δ)-uniformly learned with a sample of size*

$$m = O\left(\frac{\mathcal{VC}(\mathcal{F}) \ln \frac{1}{\epsilon} + \ln \frac{1}{\delta}}{\epsilon^2}\right).$$

Appendix C. Formal Statements of Known Revenue Guarantees for Simple Mechanisms

In various special cases, it has been shown that the aforementioned auctions earn a constant fraction of the optimal revenue. All of these results rely on buyers' valuations displaying some kind of independence across items: for additive and unit-demand buyers, this just means that for all i, $v_i = (v_{i1}, \ldots, v_{ik}) \sim \mathcal{D} = \mathcal{D}_1 \times \ldots \mathcal{D}_k$ is drawn from a product distribution. Under this assumption, Chawla et al. (2010) showed that individualized item pricings are sufficient to earn a constant fraction of optimal revenue.

Theorem 17 *[Chawla et al. (2010)] Suppose each $i \in [n]$ has a unit-demand valuation $v_i \sim \mathcal{D}_i = (\mathcal{D}_{i1} \times \ldots \times \mathcal{D}_{ik})$. Then, there exists some nonanonymous item pricing $p \in \mathbb{R}^{kn}$ such that*

$$\text{REV}(p, \mathcal{D}) \geq \frac{1}{10.67} \text{REV}(\text{OPT}).$$

For a single item-independent additive buyer, the better of the best item pricing and grand bundle pricing also earns a constant fraction of optimal revenue for that setting (Babaioff et al., 2014).

7. The upper bound stated here is a quite recent result which removes a $\ln \frac{1}{\epsilon}$ factor from the upper bound; a slightly weaker but long-standing upper bound can be attributed to Vapnik and Kotz (1982).

Theorem 18 *[Babaioff et al. (2014)] Suppose there is a single buyer which has an additive valuation $v_i \sim \mathcal{D}_i = (\mathcal{D}_{i1} \times \ldots \times \mathcal{D}_{ik})$. Then, for an item pricing $p \in \mathbb{R}^k$ and q a grand bundle price, $q \in \mathbb{R}$*

$$\max(\max_{p \in \mathbb{R}^k} \textsc{Rev}(p, \mathcal{D}_i), \max_{q \in \mathbb{R}} \textsc{Rev}(q, \mathcal{D}_i)) \geq \frac{1}{6} \textsc{Rev}(\text{OPT}, \mathcal{D}_i).$$

The final well-known result for approximately optimal Rubinstein and Weinberg (2015), "simple" revenue-maximizing mechanisms states that, for an appropriately generalized definition of valuations distributed "independently across items", one can approximately maximize revenue selling to a single subadditive buyer with item or grand bundle pricings. We now present the formal definition of independence they use for these more complicated valuation functions, and present their main result.

Definition 19 (Rubinstein and Weinberg (2015)) *A distribution $\mathcal{D}$ over valuation functions $v : 2^k \to \mathbb{R}$ is subadditive over independent items if:*

1. *All v in the support of $\mathcal{D}$ are monotone; $v(K \cup K') \geq v(K)$ for all K, K'.*
2. *All v in the support of $\mathcal{D}$ are subadditive: $v(K \cup K') \leq v(K) + v(K')$ for all K, K'.*
3. *All v in the support of $\mathcal{D}$ exhibit no externalities: there exists some $\mathcal{D}^{\boldsymbol{x}}$ over $\mathbb{R}^k$ and a function V such that $\mathcal{D}$ is a distribution that samples $\boldsymbol{x} \sim \mathcal{D}^{\boldsymbol{x}}$ and outputs v such that $v(K) = V(\{x_\kappa\}_{\kappa \in K}, K)$ for all K.*
4. *$\mathcal{D}^{\boldsymbol{x}}$ is product across its k dimensions.*

Theorem 20 *[Rubinstein and Weinberg (2015)] Suppose $\mathcal{D}_i$ is subadditive over independent items. Then, there exists a universal constant $c \geq 1$ such that*

$$\max(\max_{p \in \mathbb{R}^k} \textsc{Rev}(p, \mathcal{D}_i), \max_{q \in \mathbb{R}} \textsc{Rev}(q, \mathcal{D}_i)) \geq \frac{1}{c} \textsc{Rev}(\text{OPT}, \mathcal{D}_i).$$

Appendix D. A tighter bound on the pseudo-dimension of second-price item auctions with reserves for additive bidders

We now present a tighter analysis of second-price item auctions with reserves which exploits the total independence of buyers' behavior on items j, j'.

Theorem 21 *The pseudo-dimension of item auctions and second-price item auctions with anonymous item reserves is $O(k \log k)$ and with nonanonymous item prices/reserves is $O(nk \log(nk))$ when bidders are additive.*

Proof We present the proof for the class of second-price item auctions with item reserves; the item price result follows easily since the winner for j always pays her item price (rather than the maximum of that and the second-highest bid for j).

Rather than proving the allocation rules are linearly separable, we upper-bound the number of intermediate labelings these classes can induce for m samples, where the intermediate label space we consider is the allocation combined with, for each item, whether the winner for that item is paying the item's reserve or second price for that item. Fix some sample $S = (\mathbf{v}^1, \ldots, \mathbf{v}^m)$ where $v^t \in \mathcal{V}^n$ and $(r^1, \ldots, r^m) \in \mathbb{R}^m$.

This can be encoded in $\{0,1\}^{2k}$ for anonymous item reserves (a bit for whether or not an item is sold at its reserve and another for whether it is sold for its second-price), and $\{0,1\}^{2nk}$ for nonanonymous reserves (where each item is labeled as being allocated to some bidder, along with whether it is sold for that bidder's item-specific reserve or the second-highest bid). In the latter case, there is a post-processing rule which can reduce the label space to have size $O(n^{2k})$, since all allocations are feasible allocations. In both cases, we will use y^t to denote the intermediate label for sample $\mathbf{v}^t$.

We begin with anonymous item reserves. Since buyers are additive, we can consider each item separately. We consider item $j \in [k]$. There are $2m+1$ relevant quantities which affect the revenue any reserve achieves for item j: p_j, the reserve for j, and for each $t \in [m]$, $v^t_{i^*_j}(\{j\})$ and $v^t_{i'_j}(\{j\})$, where i^*_j, i'_j are the first and second highest bidders for j from sample t, respectively. When $p_j \leq v^t_{i'_j}(\{j\})$, let $y^t_j = 1$ and $y^t_{k+j} = 0$, when $v^t_{i^*_j}(\{j\}) \geq p_j > v^t_{i'_j}(\{j\})$, let $y^t_j = 0$ and $y^t_{k+j} = 1$, and when $p_j > v^t_{i^*_j}(\{j\})$, let $y^t_j = y^t_{n+j} = 0$. Thus, when the relative ordering of these $2m+1$ parameters is fixed, the jth and $n+j$th coordinates for all m samples are fixed. Varying p_j can induce at most $2m+2$ distinct labelings of all of S. Thus, for all k items, there are at most $(2m+2)^k$ distinct vectors $(y^1, \ldots, y^t)$.

Now, fix some intermediate labeling $(y^1, \ldots, y^m)$ of S. Then, the revenue for a particular reserve vector $(p_1, \ldots, p_k)$ which induces this labeling on the sample is easy to describe as a linear of this labeling. Namely,

$$rev(\mathbf{v}^t, \mathbf{p}, y^t) = \sum_{j : y^t_j = 1} v^t_{i'_j}(\{j\}) + \sum_{j : y^t_{n+j} = 1} \mathbf{p}_j$$

which is a linear function in $2k$ dimensions of $\mathbf{p}$ and $\mathbf{v}^t, y^t$ (which are constants). Thus, since linear functions in $2k$ dimensions have VC-dimension $2k+1$, the item reserves which agree with $(y^1, \ldots, y^m)$ can induce at most m^{2k+1} labelings of S with respect to $(r^1, \ldots, r^m)$.

Thus, the set of all item reserves can induce at most $m^{2k+1} \cdot (2m+2)^k$ labelings with respect to $(r^1, \ldots, r^m)$, so if S is shatterable it must be that $2^m \leq m^{2k+1} \cdot (2m+2)^k$, or that $m = O(k \log k)$.

With nonanonymous reserves, each sample will instead be given an intermediate label in $\{0,1\}^{nk+k}$, where there is a bit for each item/bidder pair (corresponding to whether or not that bidder wins the item and pays her individualized reserve for the item), and an additional bit for each item (corresponding to whether or not that item is sold for its second-highest bid). There are at most $[n+1]^k$ valid labelings of a single sample (each item is sold to at most one bidder, and is either sold to her at her reserve or at the second-highest price). For m samples, for a particular item j, there are now $2m+n$ parameters whose ordering matters (the highest and second-highest bids and the bidder-specific reserves for that item); the bidder-specific item reserves for that item can induce at most $(2m+n)^n$ distinct orderings of these parameters; fixing this ordering, the intermediate label is also fixed for all samples. Furthermore, once one has fixed the intermediate label for all samples, the revenues of all individualized item reserve auctions which agree with that intermediate labeling are again expressible as a linear function in $2nk$ dimensions. Thus, if the sample is shatterable, $2^m \leq (2m+n)^{nk} \cdot m^{2nk}$, implying $m = O(nk \ln(nk))$. ■

Appendix E. Omitted Proofs

Proof of Theorem 7: Consider a sample $S = (x^1, \ldots, x^m) \in \mathcal{X}^m$ of size m with targets $r = (r^1, \ldots, r^m) \in \mathbb{R}^m$. We first claim that, since $\mathcal{F}_1$ is a-dimensionally linearly separable, $\mathcal{F}_1$ can label S in at most $\binom{m}{a} \cdot |Q|^a$ distinct ways. To see this, first recall that Theorem 5 implies that $\mathcal{F}_1$ must admit a compression scheme **compress**, **decompress** of size at most a. Let $f_1(S)$ denote the labeling of all of S by some fixed $f_1 \in \mathcal{F}_1$.

Then, $\mathcal{F}_1$ can label S in at most $|\text{range}_{f_1 \in \mathcal{F}_1}(\textbf{decompress} \circ \textbf{compress})(S, f_1(S))|$ ways since this is a compression scheme for $\mathcal{F}_1$. The decompression function takes as input a *labeled* examples which are a subset of S, so it will have one of $\binom{m}{a} \cdot |Q|^a$ inputs for a fixed set S (some subset of S labeled in some arbitrary way), and therefore at most that many outputs, which upper-bounds the total number of possible labelings of S by the same quantity.

Then, fixing the labeling of S to be consistent with some $f_1 \in \mathcal{F}_1$, the pseudo-dimension of $\mathcal{F}_{2|f_1}$ is at most b (by assumption), so it can induce at most m^b many labelings of S according to r. Thus, there are at most $m^a|Q|^a m^b$ binary labelings of S with respect to r over all of $\mathcal{F}_2$ (and, therefore over all of $\mathcal{F}$). If S is shatterable, it must be that

$$2^m \leq m^a |Q|^a m^b$$

implying $m \leq (a+b)\log_2(m) + a \log_2 |Q|$, as desired. ■

Proof of Remark 9: The proof is identical to the proof of Theorem 7, with the additional application of Observation 1 to upper-bound the number of labelings that $q \circ \mathcal{F}_1$ can induce by at most $\binom{m}{a} \cdot |Q'|^a$. ■

Proof of Remark 8: For each $x \in X, y \in Q_x$, there exists $\Psi(x, y)$ and for $f \in \mathcal{F}_1$, some $w^f \in \mathbb{R}^d$ such that

$$\text{argmax}_{y \in Q_x} \Psi(x, y) \cdot w^f = f(x).$$

We simply must extend the definition of $\Psi(x, y)$ to be defined over all $y \in Q$ such that

$$\Psi(x, y') \cdot w^f < \max_{y \in Q_x} \Psi(x, y) \cdot w^f$$

for $y' \in Q \setminus Q_x$. Define $\Psi(x, y')_t = 0$ for any $t \notin T^+$, and $\Psi(x, y')_t = -1$ for all $t \in T^+$. Then, for any $y' \in Q \setminus Q_x$, $\Psi(x, y') \cdot w^f < 0$ while $\max_{y \in Q_x} \Psi(x, y) \cdot w^f \geq 0$, so the maximizing label y will be the same as before.. ■

Proof of Theorem 12: In either case, Q is a set of feasible allocations, so we only must show linear separability over the set of feasible allocations (that is, we need only show separability over labels $\mathbf{B} : \mathbf{B}_i \cap \mathbf{B}_j = \emptyset$).

We start with the first case of sequential allocations. We will show that $\mathcal{F}_1$ is an-dimensionally linearly separable. By definition, $\mathcal{F}_1$ is a set of n-wise sequential allocations from some $\mathcal{H}$ which is a-dimensionally linearly separable over $\{0, 1\}^k$. This means there exists some $\Psi : (\mathcal{V} \times \{0, 1\}^k) \times \{0, 1\}^k \to \mathbb{R}^a, w^h \in \mathbb{R}^d$ such that $\text{argmax}_B \Psi((v, X), B) \cdot w^h = h(v, X)$ for all $h \in \mathcal{H}, (v, X) \in \mathcal{V} \times \{0, 1\}^k$.

We simply need to construct some new $\hat{\Psi} : \mathcal{V}^n \times Q \to \mathbb{R}^{an}, \hat{w}^{h_1, \ldots, h_n} \in \mathbb{R}^{an}$ such that

$$\text{argmax}_{\mathbf{B}=(B_1 \ldots B_n)} \hat{\Psi}(\mathbf{v}, \mathbf{B}) \cdot \hat{w}^{h_1, \ldots, h_n} = (h_1(\mathbf{v}_1, X_1(v)), h_2(\mathbf{v}_2, X_2(\mathbf{v})), \ldots, h_n(\mathbf{v}_n, X_n(\mathbf{v}))).$$

Define $\alpha_i = 2^i H$, and define

$$\Psi((\mathbf{v}, \mathbf{B})_{ij} = \alpha_i \cdot \Psi((\mathbf{v}_i, [k] \setminus \cup_{i' < i} \mathbf{B}_{i'}) \mathbf{B}_i)_j$$

Then, for some $\prod_{(h_1, \ldots, h_n)} \in \mathcal{F}_1$, define

$$\hat{w}_{ij}^{h_1, \ldots, h_n} = w_j^{h_i}$$

Now, inspecting the dot product for some $\mathbf{v}, \mathbf{B}$ we see

$$\hat{\Psi}(\mathbf{v}, \mathbf{B}) \cdot \hat{w}^{h_1, \ldots, h_n} = \sum_i \alpha_i \Psi((\mathbf{v}_i, [k] \setminus \cup_{i' < i} \mathbf{B}_{i'}), \mathbf{B}_i) \cdot w^{h_i}$$

which, by the definition of α_i and the assumption that $\Psi((\mathbf{v}_i, X), B) \cdot w^h \leq H$ for all $\mathbf{v}_i, X, B, h \in \mathcal{H}$ implies that the maximizing label $\mathbf{B}$ will first pick $\mathbf{B}_1 \subseteq [k] = X_1(\mathbf{v})$ to maximize $\Psi((\mathbf{v}_1, X_1(\mathbf{v})), \mathbf{B}_1) \cdot w^{h_1}$, then will pick $\mathbf{B}_2 \subseteq [k] \setminus \mathbf{B}_1 = X_2(\mathbf{v})$ to maximize $\Psi((\mathbf{v}_2, X_2(\mathbf{v})), \mathbf{B}_2) \cdot w^{h_2}$, and so on. Thus, $\mathcal{F}_1$ is an-dimensionally linearly separable.

Now, suppose $\mathcal{F}_1$ is a set of n-wise repeated allocations. Since $\mathcal{H}$ is a-dimensionally linearly separable, we know that for all v, X, B_i, there exists $\Psi((v_i, X), B_i)$, and for all $h \in \mathcal{H}$ there is some w^h such that

$$\text{argmax}_{B_i} \Psi((v_i, X), B_i) \cdot w^h = h(v_i, X).$$

We simply need to define some $\hat{\Psi} : \mathcal{V}^n \times Q \to \mathbb{R}^a$, $\hat{w}^h \in \mathbb{R}^a$ such that

$$\text{argmax}_{\mathbf{B}} \hat{\Psi}(\mathbf{v}, \mathbf{B}) \cdot \hat{w}^h = (h(\mathbf{v}_1, X_1(\mathbf{v})), h(\mathbf{v}_2, X_2(\mathbf{v})), \ldots, h(\mathbf{v}_n, X_n(\mathbf{v}))).$$

Then, define

$$\hat{\Psi}(\mathbf{v}, \mathbf{B})_x = \sum_i \alpha_i \cdot \Psi((\mathbf{v}_i, [k] \setminus \cup_{i'<i} \mathbf{B}_{i'}), \mathbf{B}_i)_x$$

Then, for some $\prod_{h,\ldots,h)} \in \mathcal{F}_1$, define

$$\hat{w}^h_x = w^h_x$$

Then, the dot product

$$\Psi(\mathbf{v}, \mathbf{B}) \cdot \hat{w}^h = \sum_x \sum_i \alpha_i \cdot \Psi((\mathbf{v}_i, [k] \setminus \cup_{i'<i} \mathbf{B}_{i'}), \mathbf{B}_i)_x \cdot w^h_x = \sum_i \alpha_i \cdot \Psi((\mathbf{v}_i, [k] \setminus \cup_{i'<i} \mathbf{B}_{i'}), \mathbf{B}_i) \cdot w^h,$$

which by the definition of α_i and the guaranteed upper bound on the dot product $\Psi \cdot w^h \leq H$, we know will be maximized by first picking some $\mathbf{B}_1 \subseteq [k] = X_1(\mathbf{v})$ which maximizes $\Psi((\mathbf{v}_1, X_1(\mathbf{v})), \mathbf{B}_1) \cdot w^h$, then picking $B_2 \subseteq X_1(\mathbf{v}) \setminus h(\mathbf{v}_1, X_1(\mathbf{v})) = X_2(\mathbf{v})$ which maximizes $\Psi((\mathbf{v}_2, X_2(\mathbf{v})),\ B_2) \cdot w^h$, and so on. Thus, $\mathcal{F}_1$ is a-dimensionally linearly separable. ■

Proof of Corollary 13: We first prove first that for a single buyer, the grand-bundle mechanism is 2-dimensionally linearly separable over $\{0, 1\}$. Let $\mathcal{H}$ denote the class of single-buyer grand bundle pricings. For some $h \in \mathcal{H}$, we define $h_1 : \mathcal{V} \to \{0, 1\}$ as $h_1(v) = \mathbb{I}[v \geq p^h]$, where $p^h \in \mathbb{R}$ represents the price of the grand bundle under h. We will show $\mathcal{H}$ is 2-dimensionally linearly separable over $\{0, 1\}$. Define $\Psi(v, b) = \mathbb{I}[b = 1](v([k]), 1)$ for each $b \in \{0, 1\}$ and $w^h = (1, -p^h)$. Then,

$$\text{argmax}_b \Psi(v, b) \cdot w^h = \text{argmax}_b \mathbb{I}[b = 1](v([k] - p^f) = \mathbb{I}[v \geq p^h] = f_1(v)$$

since the penultimate expression is maximized by $b = 1$ only if $v([k]) \geq p^f$. Thus, $\mathcal{H}$ is 2-dimensionally separable.

Notice that when $\mathcal{F}$ is the set of anonymous grand bundle pricings, its allocation rules $\mathcal{F}_1$ are n-wise repeated allocations from $\mathcal{H}$. Thus, by Theorem 12, anonymous grand bundle pricings' allocations are linearly separable in 2 dimensions. The obvious intermediate label space $Q = \{\mathbf{0}\} \cup \{e_i | i \in [n]\}$, the set of standard basis vectors, contains more information than is needed to compute the revenue of these auctions.

Define $g(x) = \mathbb{I}[||x|| > 0]$. Let $\mathcal{F}'_1 = g \circ \mathcal{F}_1$. Now we prove for each $f_1 \in \mathcal{F}'_1$ that $\mathcal{F}_{2|f_1}$ has pseudo-dimension $O(1)$. Fix some $f_1 \in \mathcal{F}'_1$. Then, we have that

$$f'_2(\mathbf{v}) = f_2(g(f_1(\mathbf{v})), \mathbf{v}) = p^f \cdot f_1(\mathbf{v})$$

so, the class $\mathcal{F}_{2|g\circ f_1}$ is a class of linear functions in 1 dimensions, which have pseudo-dimension at most 2. Thus, $\mathcal{F}$ is $(2, 2, g)$-factorable over $\{0, 1\}$, and Remark 9 implies that the pseudo-dimension of anonymous grand bundle pricings is $O(1)$.

Similarly, when $\mathcal{F}$ is the the set of non-anonymous grand bundle pricings, $\mathcal{F}_1$ are n-wise sequential allocations from $\mathcal{H}$. Thus, these allocation rules are $2n$-dimensionally linearly separable, respectively. In this case, we leave the intermediate label space as $Q = \{\mathbf{0}\} \cup \{e_i | i \in [n]\}$. For any $f \in \mathcal{F}$, let $p^f \in \mathbb{R}^n$ denote the price vector for the grand bundle, that is p^f_i is i's price for purchasing the grand bundle. Fix some $f_1 \in \mathcal{F}_1$; we claim that $\mathcal{F}_{2|f_1}$ has pseudo-dimension $O(n)$. For any $f'_2 \in \mathcal{F}_2$ and any f which is decomposed into (f_1, f_2) , we have that $f'_2(\mathbf{v}) = f_2(f_1(\mathbf{v}), \mathbf{v}) = p^f \cdot f_1(v)$, which again is a linear function when f_1 is fixed, in this case in n dimensions. Thus, $\mathcal{F}$ is $(2n, n)$-factorable over Q, so Theorem 7 implies that the pseudo-dimension of nonanonymous grand bundle pricings is $O(n \log n)$. ■

Proof of Corollary 14: As in the previous proof, we claim that $\mathcal{F}_1$, the allocation rules of these auctions are n-wise repeated allocations and n-wise sequential allocations from the single-buyer item pricings allocation set $\mathcal{H}$. We begin by showing $\mathcal{H}$ is $k + 1$-dimensionally linearly separable. For some $h \in \mathcal{H}$, let $p^h \in \mathbb{R}^n$ denote the item pricing faced by the single buyer. Then, define for $v \in \mathcal{V}$, $B \in \{0, 1\}^k$,

$$\Psi(v, B)_j = \begin{cases} \mathbb{I}[j \in B] & \text{if } j \in [k] \\ v(B) & \text{if } j = k + 1 \end{cases}$$

and for $h \in \mathcal{H}$, define

$$w^h_j = \begin{cases} -p^h_j & \text{if } j \in [k] \\ 1 & \text{if } j = k + 1\ . \end{cases}$$

Then, we have that $\Psi(v, B) \cdot w^h = v(B) - \sum_{j\in B} p^h_j$, which will be maximized by B which maximizes v's utility. Thus, $h(v) = \text{argmax}_B v(B) - \sum_{j\in B} p^h_j = \text{argmax}_B \Psi(v, B) \cdot w^h$, so $\mathcal{H}$ is $k + 1$-dimensionally linearly separable.

Consider $\mathcal{F}$ the class of anonymous item prices. Theorem 12 implies that this class is $k+1$-dimensionally linearly separable over $Q = [n]^k$. Again, the intermediate label space suggested by this reduction to the single-buyer case, $Q = [n]^k$, is larger than necessary to compute revenue. Define $g(\mathbf{B})_j = \mathbb{I}[j \in \cup_i \mathbf{B}_i]$ and $Q' = \{0, 1\}^k$. We now show that, for a fixed $f_1 \in \mathcal{F}_1$, the class $\mathcal{F}_{2|g\circ f_1}$ has pseudo-dimension $O(k)$. Notice that for any $f'_2 \in \mathcal{F}_{2|g\circ f_1}$, we have that

$$f'_2(\mathbf{v}) = f_2(g(f_1(\mathbf{v})), \mathbf{v}) = p^f \cdot f_1(v)$$

which, again is a k-dimensional linear function for some fixed f_1, and therefore has pseudo-dimension at most $k + 1$. Thus, the class $\mathcal{F}$ can be $(k + 1, k + 1, g)$-factored over $\{0, 1\}^k$, and Remark 9 implies the pseudo-dimension is thus at most $O(k^2)$.

The proof for the nonanonymous case is identical, with two changes. First, $\mathcal{F}_1$ is a set of n-wise sequential allocations, so it is linearly separable in $n(k + 1)$ dimensions. Second, we cannot compress the intermediate label space $Q \subset \{0, 1\}^{nk}, |Q| \le [n]^k$, since $f'_2(\mathbf{v}) = f_2(f_1(\mathbf{v}), \mathbf{v}) = p^f \cdot f_1(v)$ only expresses the revenue of the auction if $f_1(v)$ expresses which buyers purchase which items; thus, the set $\mathcal{F}_{2|f_1}$ has pseudo-dimension at most $O(nk)$. Thus, the class $\mathcal{F}$ can be $(O(nk), O(nk))$-factored over Q with $|Q| \le [n]^k$, and Theorem 7 implies the pseudo-dimension is thus at most $O(nk^2 \ln(n))$. ■