Strategic Representation

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ABSTRACT

Humans have come to rely on machines for reducing excessive information to manageable representations. But this reliance can be abused—strategic machines might craft representations to manipulate their users. How can a user make good choices on strategic representations? We formalize this as a learning problem, and pursue algorithms for decision-making that are robust to manipulation. In our main setting of interest, the system represents attributes of an item to the user, who decides whether or not to consume. We model this interaction through the lens of strategic classification (Hardt et al. 2016), but *reversed*: the user, who learns, plays first; and the system, which responds, plays second. The system must respond with representations that reveal 'nothing but the truth', but need not reveal the entire truth; thus, the user faces the problem of learning set functions under strategic constraint. This presents distinct algorithmic and statistical challenges. Our main result is a learning algorithm that minimizes error despite strategic representations, and our analysis sheds light on the trade-off between learning effort and susceptibility to manipulation.

KEYWORDS

Strategic Learning, Strategic Classification, Gaming, Strategic Representation

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1 INTRODUCTION

Strategic classification tells the story of how learning systems are susceptible to 'gaming' by self-interested users. But the reverse scenario—in which it is the system that strategically games its users—is quite routine. In settings where users make choices about items (e.g., click, buy, watch), systems often hold the power to determine how items are *represented*—a power they can utilize to promote their own goals. In this paper we formalize this scenario of *strategic representation*, and study how learning can aid users in choosing well despite strategic system behavior.

As a concrete example, consider a hotel booking platform, in which a hotel is presented to the user alongside a small set of representative images. As there are many images available for each hotel, the system must choose which subset of these to display. Clearly, the choice of representation can have a significant effect on user decision-making (whether to click the hotel and even whether to book it), and therefore on the system's profit. The system may well attempt to capitalize on the control it has over what information is presented to the user in order to increase its profit, at the expense of the user who will reach sub-optimal decisions. Given the deep dependence of users on systems for information, it is important that the way in which they learn to respond to representations take into account the systems' strategizing.

Our formalization. We model the interaction between the system and user as a Stackelberg game, where the user leads by fixing a *choice* strategy h, and the system best-responds with a representation. The user's 'strategy' is the way she routinely acts upon representations (e.g., which representations she chooses to click on). As argued in Zrnic et al. [28], users (agents in their language) are typically consistent in their online behavior, whereas systems (platforms) are characterized by "dominant computational power and abundant data resources, allowing the platform to react to any change in the agents' behavior virtually instantaneously." This makes the system the natural follower/best-responder to the user's foreseen choices in the interaction.

We focus on discrete items, each composed of a subset of ground elements. In reality, a full description of item x is often too large for humans to process effectively, and so systems provide them with a compact representation, $\phi(x)$. We consider representation mappings ϕ that are lossy but *truthful*, meaning they reveal a cardinality-constrained subset of the item's full set of attributes: $\phi(x) \subseteq x$ and $k_1 \leq |\phi(x)| \leq k_2$. In other words, representations need not be 'the whole truth', but must include 'nothing but the truth.' Examples include retail items described by a handful of attributes; videos presented by several key frames; and movie recommendations described by a select set of reviews.

The user wishes to choose items that are 'worthwhile' to her, as determined by her valuation function—in our case, a set function, which can reflect complex tastes (e.g., account for complementarity, such as 'balcony' and 'ocean view'). Meanwhile, the system aims to maximize user engagement by presenting to the user a subset of attributes (satisfying cardinality constraints) that will lead her to choose the item. This misalignment in goals causes friction: while a representation may be optimal for the system, it does not necessarily align with the interests of the user. Importantly, while values are based on the true attributes x, choices rely on the observed attributes $\phi(x)$, which the system controls.

A range of user behaviors. Users naturally have access to their personal past experiences (which we model as samples), and by anticipating the system to be strategic, can use these to learn which items to choose, and which to skip. Many users however will lack the capacity (or desire) to take into account the system's manipulation; these will naïvely take representations at face value, and choose according to whether $\phi(x)$ seems worthwhile to them. More sophisticated users will indeed learn to classify items, hopefully in a way that is robust to manipulation by the system. But the degree of robustness depends on their computational resources, the amount of data they hold, and the sophistication of their tastes. We will therefore allow the user control over a parameter k, which we think of as a 'knob' determining the the amount of effort invested in learning.

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Our central learning question is: how can the user learn a classifier that is compatible with her valuation despite manipulation? We are also interested in how effort level k together with the representation constraints k_1, k_2 influence the balance of powers among user and system. For example, it is not hard to show that a naïve user will be severely gamed by the system (Sec. 3). How much can she gain by learning a classifier of 'complexity' k? We demonstrate that even modest ks can dramatically increase user payoff.

1.1 Overview of our results and organization

Our main result is the user's learning algorithm in Sec. 4 (see Algo. , Thm. 4.7), which minimizes the empirical error over a hypothesis family of classifiers with complexity k (the degree of synergies—like complements—that can be taken into account when classifying the system's representation). The algorithm builds upon several structural results we establish for binary classifiers that operate on sets, e.g., that it suffices to use simple-form set functions even when taking into account the system's strategic response (Thm. 4.6).

In terms of the interplay between k, k_1, k_2, our results in Sec. 5 show the following: For fixed representation range $[k_1, k_2]$, the larger the complexity k, the better the user's payoff, because learned functions are more expressive and can better approximate the valuation v. Thm. 5.4 shows that when the complexity matches that of the user's valuation, the approximation error vanishes. On the other hand, a large k is costly in running time and in data—it means larger sample complexity and so larger estimation error (Thm. 5.9). We thus get a tradeoff controlled by the user's effort level k. Now keep the complexity k fixed and let the system control k_1, k_2. Perhaps surprisingly, the system can increase its payoff by 'tying its hands' to a lower k_2. This is because k_2 upper-bounds not only the system's range but also the 'effective' k of the user (who gets nothing from choosing $k > k_2$), and the lower the k, the better it is for the system (see Lem. 5.10). We discuss take-aways in Sec. 6.

1.2 Related Work (See Also Appx. B)

Relation to strategic classification. Our formalization of strategic representation shares a deep connection to strategic classification (SC) [15], a very active area of research—e.g. [8, 16, 23, 26, 27]. Both models have the same structure (a leading learning player who must take into account a strategic responder), but there are important differences. The first is conceptual – the roles of the system and the user are reversed.[1] E.g., in SC the system aims to learn an accurate classifier, whereas in our setting it is the user who learns. The implications of this change are mainly to the balance of power between the sides (see Sec. 5). The second difference is that the objects being classified are discrete in our setting rather than continuous, and their manipulation is only by hiding information (in the language of SC, we fix a particular cost function—distinct from the standard ones in the literature). From a learning perspective, whereas SC considers 'conventional' learning of vector functions, strategic representation focuses on learning *set functions*. We view the close connection to SC as a strength of our formalization – it shows that the SC setup is useful far beyond what was previously considered; and also that a fairly mild variation leads to a completely different learning problem, with distinct algorithmic and statistical challenges. SC works closest to ours are by Zrnic et al. [28], who change the order of play (while we switch the roles); and by Krishnaswamy et al. [19], who study masking attributes by the user (rather than dropping attributes by the system), and aim for classifiers that incentivize 'the whole truth' (while we aim to correctly classify despite manipulation).

Relation to Bayesian persuasion. In Bayesian persuasion [18], a more-informed player uses its information advantage coupled with commitment power to influence the choices of a decision-making player. The more-informed player moves first, committing to a scheme for signaling information (equiv., for recommending an action) to the decision-maker. This fits a scenario in which the system knows the user valuation and there is common knowledge of D, and this knowledge can be used to persuade (recommend an action to) the user. In our work, the order is reversed—the decision-maker (user) moves first and the more-informed player (system) follows—and the knowledge assumptions are more relaxed. Since who leads and who follows is determined by the relative frequencies at which the system and user adapt to each other's actions [28], both scenarios are well-worth studying. Bayesian persuasion works closest to ours are by Dughmi et al. [9], who upper bound the number of signaled attributes, and by Haghtalab et al. [14], who study strategic selection of anecdotes. In both these works as in ours, the human player is a learner.

Strategic disclosure of information in economics. Strategic disclosure to influence decision-making has long been studied in economics [12, 13, 17, 22], motivated by information "shrouding" being common in practice [5, 21]. This classic line of work has no element of learning. Also, the studied settings are usually quite different from ours, leading to different conclusions. For example, Milgrom [22] proposed a sequential-game formulation, where a salesman (system) moves first and strategically discloses product attributes, then a rational customer (user) decides whether to purchase based on the information revealed. The preferences of the customer are known to the salesman (unlike our setting in which preferences are revealed through strategic choices of the user), and the system adjusts its information revelation accordingly. The recent work of Haghtalab et al. [14] can also be viewed as part of this literature, and it also assumes the information sender moves first (where in their case the information is a carefully selected anecdote), rather than reacts to the information receiver.

2 A FORMALIZATION OF STRATEGIC REPRESENTATION

Strategic representation setting. Consider two players—a user and a system. The system shows the user a *representation* z of an item x drawn from some unknown distribution D, and the user decides whether or not to accept this item (e.g., click, buy or watch it). Formally, a strategic representation setting $(E, \mathcal{X}, D, k_1, k_2, v)$ is composed of the following: a ground set E of q possible item attributes; a collection of items $\mathcal{X} \subseteq 2^E$ where an item $x \in \mathcal{X}$ is defined as a subset of up to n attributes; an arbitrary distribution D over items $\mathcal{X}$; upper and lower bounds $k_1, k_2 \in \mathbb{N} \cup \{0\}, k_1 \leq k_2$ on the size of an item's representation; and the user's value

[1] Our notions of system and user mirror practice – the system controls the platform where the interaction takes place, whereas the user is the (usually human) player using the platform.

function $v : 2^E \to \mathbb{R}$ over subsets of attributes. For simplicity we assume that each item has at least κ attributes and $k_1 \leq \kappa$. Let $\mathcal{Z} = \{z \in 2^E : \exists x \in \mathcal{X}, z \subseteq x, |z| \in [k_1, k_2]\}$ be the space of valid item representations, i.e., the collection of all subsets of items of size between k_1 and k_2. Let $y = y(x) = \text{sign}(v(x))$ indicate whether the item's value to the user is positive ($y = 1$) or not ($y = -1$). We say an item is *worthwhile* to the user if $v(x) \geq 0$ (equiv., $y = 1$). Throughout we assume the user (who learns) has sample access to D, on which we make no assumptions. We also make the standard assumption of the user having oracle access to the valuation function v, but note that our main results (Sec. 4-5) hold even under sample access to v.

Example. Our above setting originates from the seminal work in consumer theory by Lancaster [20], who proposed to view consumer goods as a collection of attributes. The cardinality constraints k_1, k_2 on the representation size are also motivated by realistic considerations, like physical restrictions (e.g., screen size) or cognitive limitations (e.g., information processing capacity). For example, consider a system recommending a book x to a user. The book can be summarized as a collection of attributes from E such as "happy ending" or "books made into movies". Value depends on a complete characterization of the book; but this likely includes a very large number of attributes (n). The platform's interface only permits a small, manageable number of attributes ($k_2 \ll n$) to be presented on screen (e.g., in search results). Nonetheless, the choice of *which* subset of attributes to present ($z \subset x$), and how many ($|z| \in [k_1, k_2]$), is in the hands of the system. The user must make her choice based on this partial representation, using her previous experiences (i.e., a sample set) to guide her decisions.

2.1 Strategic representation as a game

Action spaces. Both players are assumed to be (potentially) strategic about their choices: The user chooses whether or not to accept an item based on its representation $z \in \mathcal{Z}$; the system chooses an item's representation based on its full attributes $x \in \mathcal{X}$. We denote by $h : \mathcal{Z} \to \{\pm 1\}$ the user's strategy, called her *choice function*, and by $\phi : \mathcal{X} \to \mathcal{Z}$ the system's strategy, called its *representation mapping*. We require ϕ to output representations that, while possibly lossy, are guaranteed to be truthful. Formally, a representation z is *truthful* if it includes only attributes that appear in x, i.e., $z \subseteq x$, and is *lossy* if $z \subset x$. If $k_2 < |x|$ then z is necessarily lossy. The requirement of truthfulness mirrors realistic considerations—an untruthful system which intentionally distorts information is unlikely to attract users in the long run. Intuitively, truthfulness gives users some hope of resilience to manipulation, whereas k_1, k_2 control how much leeway the system has in revealing only partial truths.

Preferences. The user would like to choose an item if and only if it is worthwhile to her, i.e., if $y = 1$ (an optimal choice function h thus satisfies $h(z) = y$). However, while an item's value is determined by its full description x, the user's choice must be based on partial information z. The main challenge is that representations are controlled by the system, who is interested in maximizing user "engagement", i.e., mapping x to $\phi(x) = z$ such that the user accepts ($h(z) = 1$). For example, the system could strategically choose not to reveal attributes (e.g., "historical novel") that would lead the user to reject the item.

The game. We model the interaction between the user and system as a Stackelberg game that proceeds as follows. The user moves first: Initially, she observes a sample set $S = \{(x_i, y_i)\}_{i=1}^m$ of items and their worthwhileness to her (in our example, this sample set would be previously read books), where $x_i \sim D$ and $y_i = \text{sign}(v(x_i))$.Then, and possibly using these samples, the user decides on and commits to a choice function h. The system moves second, and given h chooses a representation mapping ϕ_h (note the dependence of ϕ_h on h). The order of the players reflects the ability of the system to move quickly, adapting to the user's strategy [28].

In accordance to their preferences, we model the players' expected payoffs in the game upon playing (h, ϕ_h) as:

$$\textbf{User:} \quad \mathbb{E}_{x\sim D}[\mathbb{1}\{h(\phi_h(x)) = y\}]; \tag{1}$$

$$\textbf{System:} \quad \mathbb{E}_{x\sim D}[\mathbb{1}\{h(\phi_h(x)) = 1\}]. \tag{2}$$

User's payoff is the expected worthwhileness of choices; system's payoff is the expected user engagement.

System behavior. The system maximizes its payoff by playing a *best-response* representation mapping, which satisfies

$$\phi_h(x) = \operatorname*{argmax}_{z\subseteq x, |z|\in[k_1,k_2]} h(z). \tag{3}$$

From now on we overload notation and by $\phi_h(x)$ refer to this best-response mapping. Note that since h is binary, the argmax may not be unique (e.g., if some $z_1 \subseteq x, z_2 \subseteq x$ both have $h(z_1) = h(z_2) = 1$), but the particular choice of z does not matter—from the user's perspective, her choice of h is invariant to the system's choice of best-response z (proof given in Appx. C).

Observation 2.1. *In a strategic representation game, every best-response $z \in \phi_h(x)$ induces the same expected payoff to the user.*

User behavior. Given that the system best-responds to the user, the user's choice function h determines her payoff. We denote the user's expected payoff from playing h by

$$U(h) = \mathbb{E}_{x\sim D}[\mathbb{1}\{h(\phi_h(x)) = y\}].$$

The user thus seeks to maximize the probability that $h(z) = y$. This makes the task of finding a good h using the samples $S = \{(x_i, y_i)\}_{i=1}^m$ one of learning an accurate classifier (with "accept" and "reject" classes) that is robust to strategic manipulation. Robustness is necessary since the learned classifier is applied not to x but to its strategic representation z. Realistically, not all users are learners (let alone robust). We study three kinds of user types, increasing in sophistication and in the amount of effort invested in determining h.

The naïve user: This user plays h that satisfies $h(z) = \text{sign}(v(z))$ for every $z \in \mathcal{Z}$ as her choice function. This models users who systematically take the system's representation at face value, and so either accept or reject an item based on the value they associate with its representation.

The agnostic user: Makes no assumptions about the system. This user employs a simple strategy that relies on basic data statistics which provides minimal but robust guarantees regarding her payoff.

The strategic user: Knows that the system is strategic, and anticipates it to best-respond to h. This user is willing to invest effort (in terms of data and computation) in learning a choice function

h that improves her payoff by accounting for the system's strategic behavior. In fact, we consider a series of strategic users with increasing learning efforts.

3 WARM-UP: NAÏVE AND AGNOSTIC USERS

The naïve user. The *naïve user* employs a 'what you see is what you get' policy: given a representation of an item, z, this user estimates the item's value based on z alone, acting 'as if' z were the item itself. Consequently, the naïve user sets $h(z) = \text{sign}(v(z))$, even though v is truly a function of x. The naïve user fails to account for the system's strategic behavior (let alone the fact that $z \subseteq x$ of some actual x).

Despite its naivety, there are conditions under which this user's approach makes sense. Our first result shows that the naïve policy is sensible in settings where the system is *benevolent*, and promotes user interests instead of its own.

Lemma 3.1. *If system plays the* benevolent *strategy:*

$$\phi_h^{\text{benev}}(x) = \underset{z \subseteq x, |z| \in [k_1, k2]}{\text{argmax}} \{\mathbb{1}\{h(z) = \text{sign}(v(x))\},$$

then the naïve approach maximizes user payoff.

Proof in Appx. D. The above lemma is not meant to imply that naïve users *assume* the system is benevolent; rather, it justifies why users having this belief might act in this way. Real systems, however, are unlikely to be benevolent; our next example shows a strategic system can easily manipulate naïve users to receive arbitrarily low payoff.

Example 1. Let $x_1 = \{a_1\}, x_2 = \{a_1, a_2\}, x_3 = \{a_2\}$ with $v(x_1) = +1$ and $v(x_2) = v(x_3) = -1$. Fix $k_1 = k_2 = 1$, and let $D = (\varepsilon/2, 1-\varepsilon, \varepsilon/2)$. Note $\mathcal{Z} = \{a_1, a_2\}$ are the feasible representations. The naïve user assigns $h = (a_1) = +1, h(a_2) = -1$ according to v. For x_2, a strategic system plays $\phi(x_2) = a_1$. The expected payoff to the user is ε.

One reason a naïve user is susceptible to manipulation is because she does not make any use of data she may have. We next describe a slightly more sophisticated that does.

The agnostic user. The *agnostic user* puts all faith in data; this user does not make assumptions on, nor is she susceptible to, the type of system she plays against. Her strategy is simple: collect data, compute summary statistics, and choose to either always accept or always reject (or flip a coin). In particular, given a sample set $S = \{(x_i, y_i)\}_{i=1}^m$, the agnostic user first computes the fraction of positive examples, $\hat{\mu} := \frac{1}{m}\sum_{i=1}^m y_i$. Then, for some tolerance τ, sets for *all* z, $h(z) = 1$ if $\hat{\mu} \geq 1/2 + \tau$, $h(z) = -1$ if $\hat{\mu} \leq 1/2 - \tau$, and flips a coin otherwise. In Example 1, an agnostic user would choose $h = (-1, -1)$ when m is large, guaranteeing a payoff of at least $\frac{\sqrt{m}(1-\varepsilon/2)}{2+\sqrt{m}} \to (1 - \varepsilon/2)$ as $m \to \infty$. Albeit investing minimal effort, for an appropriate choice of τ, this user's strategy turns out to be quite robust.

Theorem 3.2. *(Informal) Let μ be the true rate of positive examples, $\mu = \mathbb{E}_D[y]$. Then as m increases, the agnostic user's payoff approaches $\max\{\mu, 1-\mu\}$ at rate $1/\sqrt{m}$.*

Formal statement and proof in Appx. A.1. In essence, the agnostic user guarantee herself the 'majority' rate, and in a way that does not depend on how system responds, with rudimentary usage of her data. But this is can be far from optimal; we now turn to the more elaborate *strategic user* who makes more clever use of the data at her disposal.

4 STRATEGIC USERS WHO LEARN

A strategic agent acknowledges that the system is strategic, and anticipates that representations are chosen to maximize her own engagement. Knowing this, the strategic user makes use of her previous experiences, in the form of a labeled data set $S = \{(x_i, y_i)\}_{i=1}^m$, to learn a choice function $\hat{h}$ from some function class H that optimizes her payoff (given that the system is strategic). Cast as a learning problem, this is equivalent to minimizing the expected classification error on strategically-chosen representations:

$$h^* = \underset{h \in H}{\text{argmin}}\, \mathbb{E}_D[\mathbb{1}\{h(\phi_h(x)) \neq y\}] \tag{4}$$

Since the distribution D is unknown, we follow the conventional approach of empirical risk minimization (ERM) and optimize the empirical analog of Eq. (4):

$$\hat{h} = \underset{h \in H}{\text{argmin}}\, \frac{1}{m}\sum_{i=1}^m h(\phi_h(x_i)) \neq y_i) \tag{5}$$

Note that since the $z_i = \phi_h(x_i)$ are sets, H must include *set functions* $f : \mathcal{Z} \to \{\pm 1\}$, and any algorithm for optimizing Eq. (5) must take this into account.

We begin this section with some useful definitions and results, these setting the stage for our algorithm and analysis.

4.1 Complexity classes of set functions

Ideally, a learning algorithm should permit flexibility in choosing the complexity of the class of functions it learns (e.g., the degree of a polynomial kernel, the number of layers in a neural network), as this provides means to trade-off runtime with performance and to reduce overfitting. In this section we propose a hierarchy of set-function complexity classes that is appropriate for our problem. Throughout we will denote by $\Gamma_k(z)$ all subsets of z of size at most k, i.e:

$$\Gamma_k(z) = \{z' \in \mathcal{Z} \,:\, z' \subseteq z, |z'| \leq k\}$$

We start with a structural definition—see also [7] and Appx. B.

Definition 4.1. We say the function $h : \mathcal{Z} \to \{\pm 1\}$ is of *order* k if there exist weights of cardinality at most k, $\boldsymbol{w} = \{w(z') \,:\, z' \in \Gamma_k(z)\}$, such that

$$h(z) = \text{sign}\left(\sum_{z' \in \Gamma_k(z)} w(z')\right)$$

Our next result shows that, in the context of optimizing Eq. (5), working with k-order functions is sufficiently general.

Lemma 4.2. *For any $h : \mathcal{Z} \to \{\pm 1\}$, there exists a $k \leq k_2$ and a corresponding k-order function h' such that:*

$$h(\phi_h(x)) = h'(\phi_{h'}(x))\,.$$

Proof in Appx. E. Lem. 4.2 shows that, for learning purposes, any set function h can be linked to a matching k-order function h' (for some k) through how it operates on strategic inputs. We henceforth focus on k-order functions.

The proof of Lem. 4.2 is constructive, and the construction itself turns out to be highly useful. In particular, the proof uses h' having

a particular form of *binary* basis weights, $w(z) \in \{a_-, a_+\}$, which we henceforth assume are fixed. Hence, all functions h have corresponding binary-weighted k-order functions h', which motivates the following definition of functions and function classes.

Definition 4.3. We say a k-order function h with basis weights $\boldsymbol{w}$ is *binary-weighted* if:

$$w(z) \begin{cases} \in \{a_-, a_+\} & \forall z = k \\ = a_- & \forall z < k \end{cases}$$

for some fixed choice of $a_- < -1$ and $a_+ > \sum_{i\in[k]} \binom{n}{k}$, and the class of all binary-weighted k-order functions is:

$$H_k = \{h \,:\, h \text{ is a binary-weighted } k\text{-order function}\}$$

The classes H_k will serve as complexity classes for our algorithm; the user provides k as input, and the algorithm outputs an $\hat{h} \in H_k$ that minimizes the empirical loss. As we will show, using k as a complexity measure provides the user direct control over the tradeoff between estimation error and approximation error, as well as over runtime.

Next, we show that the H_k classes are strictly nested. This will be important for our analysis of approximation error, as it will let us reason about the connection between the learned $\hat{h}$ and the target function v.

Lemma 4.4. *For all k, $H_k \subset H_{k+1}$ and $H_{k+1} \setminus H_k \neq \emptyset$.*

Proof. Arbitrarily choose a $u \subset E$ (recall E is the ground set) such that $|u| = k$, and let $w(u) = a_{k,+} > \sum_{i\in[k]} \binom{n}{i}$. Also for all $z \neq u$ and $|z| \leq k$, let $w(z) = a_- \in (-1, 0)$. Let $h : \mathcal{Z} \to \{\pm 1\}$ be defined as follows

$$h(z) = \text{sign}\left(\sum_{z':z'\subseteq z, |z'|\leq k} w(z')\right).$$

It is easy to see that $h \in H_k$. We show that $h \notin H_{k-1}$. First, observe that for all $z \in \mathcal{Z}$ $h(z) = 1$ if and only if $u \subseteq z$. Suppose $h \in H_{k-1}$. Then there is a weight function w' on sets of size at most $k-1$ such that either $w'(z) = a_- \in (-1, 0)$ or $w_z = a_{k-1,+} > \sum_{i\in[k-1]} \binom{n}{i}$, and

$$h(z) = \text{sign}\left(\sum_{z':z'\subseteq z, |z'|\leq k-1} w'(z')\right).$$

Let $z \in \mathcal{Z}$ be such that $u \subset z$. This implies $h(z) = 1$. Hence there exist a $u' \subset z$ such that $|u'| = k-1$ and $w'(u') = a_{k-1,+}$. Let $\tilde{z} \in \mathcal{Z}$ be such that $u' \subset z'$ but $u \not\subset \tilde{z}$. Such a $\tilde{z}$ exists because $u \cap u' \neq u$. Further, as $u \not\subset \tilde{z}$, we have $h(z') = -1$. But since $u' \subseteq \tilde{z}$, we have from the choice of $a_{k-1,+}$ and a_-

$$\sum_{z':z'\subseteq z, |z'|\leq k-1} w'(z') \;>\; 0$$
$$\Rightarrow \text{sign}\left(\sum_{z':z'\subseteq z, |z'|\leq k-1} w'(z')\right) \;=\; h(\tilde{z}) \;=\; 1.$$

This gives a contradiction. Hence, $h \notin H_{k-1}$. □

Note that H_n includes all binary-weighted set functions, but since representations are of size at most k_2, it suffices to consider only $k \leq k_2$. Importantly, k can be set lower than k_1; for example, H_1 is the class of threshold modular functions, and H_2 is the class of threshold pairwise functions. The functions we consider are parameterized by their weights, $\boldsymbol{w}$, and so any k-order function has at most $|\boldsymbol{w}| = \sum_{i=0}^{k} \binom{q}{i}$ weights. In this sense, the choice of k is highly meaningful. Now that we have defined our complexity classes, we turn to discussing how they can be optimized over.

4.2 Learning via reduction to induced functions

The simple structure of functions in H_k makes them good candidates for optimization. But the main difficulty in optimizing the empirical error in Eq. (5) is that the choice of h does not only determine the error, but also determines the inputs on which errors are measured (indirectly through the dependence of ϕ_h on h). To cope with this challenge, our approach is to work with *induced* functions that already have the system's strategic response encoded within, which will prove useful for learning. Additionally, as they operate directly on x (and not z), they can easily be compared with v, which will become important in Sec. 5.

Definition 4.5. For a class H, its *induced class* is:

$$F_H \triangleq \{f : \mathcal{X} \to \{\pm 1\} \,:\, \exists h \in H \text{ s.t. } f(x) = h(\phi_h(x))\}$$

The induced class F_H includes for every $h \in H$ a corresponding function that already has ϕ_h integrated in it. We use $F_k = F_{H_k}$ to denote the induced class of H_k. For every h, we denote its induced function by f_h. Whereas h functions operate on z, induced functions operate directly on x, with each f_h accounting internally for how the system strategic responds to h on each x.

Our next theorem provides a key structural result: induced functions inherit the weights of their k-order counterparts.

Theorem 4.6. *For any $h \in H_k$ with weights $\boldsymbol{w}$:*

$$h(z) = \text{sign}\left(\sum\nolimits_{z'\in\Gamma_k(z)} w(z')\right),$$

its induced $f_h \in F_k$ can be expressed using the same weights, $\boldsymbol{w}$, but with summation over subsets of x, i.e.: $f_h(x) = \text{sign}\left(\sum_{z\in\Gamma_k(x)} w(z)\right)$.

Proof. Since $h \in H_k$, w satisfies the following two properties (see Definition 4.3):

(1) either $w(z) = a_- \in (-1, 0)$ or $w(z) = a_+ > \sum_{i\in[k]} \binom{n}{i}$
(2) $w(z) = a_-$ for all z having $|z| < k$

Further from the definition of f_h, we have $f_h(x) = h(\phi_h(x))$. This implies

$$f_h(x) = 1 \iff \exists z \in \mathcal{Z},\, z \subset x \text{ such that } h(z) = 1$$

Finally from the the above two properties of the weights function, we have

$$h(z) = 1 \iff \exists z' \subseteq z,\, |z'| = k \text{ such that } w(z') > 0$$

From the above two equations we conclude

$$f_h(x) = 1 \iff \exists\, z \subset x, |z| = k \text{ such that } w(z) > 0$$

Finally, the two properties of w ensure

$$f(x) = \text{sign}\left(\sum\nolimits_{z:z\subseteq x, |z|\leq k} w(z)\right).$$

□

Thm. 4.6 is the main pillar on which our algorithm stands: it allows us to construct h by querying the loss *directly*—i.e., without explicitly computing ϕ_h—by working with the induced f_h; this is since:

$$\mathbb{1}\{h(\phi_h(x_i)) \neq y_i\} = \mathbb{1}\{f_h(x_i) \neq y_i\}$$

Algorithm: ALG

Input: $S = \{(x_i, y_i)\}_{i\in[m]}$, $k \in [k_2]$
Pre-compute:
$S^+ = \{x \in S : y = +1\}$, $S^- = \{x \in S : y = -1\}$
$Z_{k,S} = \{z : |z| = k, \exists x \in S\ z \subseteq x\}$
$\hat{p}(x_i) = \frac{1}{m}\sum_{j\in[m]} \mathbb{1}\{x_i = x_j\} \quad \forall i \in [m]$
Fix $a_- \in (0,1)$ and $a_+ > \sum_{i\in[1,k]} \binom{n}{i}$
Initialize:
$Z^+ = \emptyset$, $Z^- = \emptyset$, $V = \emptyset$, $S_z = \emptyset \quad \forall z \in Z_{k,S}$
Run:
1. **for** $x \in S^-$ **do**
  2. **for** z s.t. $z \subseteq x$ and $z \in Z_{k,S}$ **do**
    3. $Z^- = Z^- \cup \{z\}$, $Z_{k,S} = Z_{k,S} \setminus \{z\}$
    4. $S_z = S_z \cup \{x\}$
5. **for** $x \in S^+$ **do**
  6. **if** $\exists\, z \subseteq x$ and $z \in Z_{k,S}$ **then**
    7. **for** $z \subseteq x$ such that $z \in Z_{k,S}$ **do**
      8. $Z^+ = Z^+ \cup \{z\}$
  9. **else**
    10. **for** z s.t. $z \subseteq x$ and $z \in Z^-$ **do**
      11. $V = V \cup \{z\}$
      12. $S_z = S_z \cup \{x\}$
13. Compute $\mu(z) = \sum_{x\in S_z} \hat{p}(x)y$ for all $z \in V$
14. **while** $\nexists z \in V$ such that $\mu(z) \geq 0$ **do**
  15. Compute $z^* = \text{argmax}_{z\in V}\, \mu(z)$
  16. $Z^+ = Z^+ \cup \{z^*\}$, and $Z^- = Z^- \setminus \{z^*\}$
  17. $V = V \setminus z^\star$, 18. $S_z = S_z \setminus S_{z^\star}$ for all $z \in V$
  19. Recompute $\mu(z)$ for all $z \in V$
20. Set $w(z) = \begin{cases} a_+ & \text{if } z \in Z^+ \\ a_- & \text{o.w. (implicitly)} \end{cases}$ ▷ *implemented as hash table*
return $\hat{h}(z) = \text{sign}(\sum_{z'\in\Gamma_k(z)} w(z'))$.

Thus, through their shared weights, induced functions serve as a bridge between *what* we optimize, and *how*.

4.3 Learning algorithm

We now present our learning algorithm, ALG. The algorithm is exact: it takes as input a training set S and a parameter k, and returns an $h \in H_k$ that minimizes the empirical loss (Eq. (5)). The algorithm constructs h by sequentially computing its weights, $\boldsymbol{w} = \{w(z)\}_{|z|\leq k}$. As per Def. 4.3, only $w(z)$ for z with $|z| = k$ must be learned; hence, weights are sparse, in the sense that only a small subset of them are assigned a_+, while the rest are a_-. Weights can be implemented as a hash table, where $w(z) = a_+$ if z is in the table, and $w(z) = a_-$ if it is not. To assign optimal weights, the algorithm executes a series of queries to the loss function. Due to Thm. 4.6, the algorithm need not compute the loss directly on h; rather, as per the shared-weight structure of k-order and induced functions, it can efficiently compute the loss indirectly in induced space. We next prove correctness and runtime for ALG.

Theorem 4.7. *For any $k \in [k_2]$, ALG returns an $h \in H_k$ that minimizes the empirical loss in Eq. (5).*

Proof in Appx. E.1. The main challenge here lies in showing that it suffices to work only with weights for z of size exactly k, even though the output function h must provide guarantees for all z of size $|z| \in [k_1, k_2]$. For this, we use a certain 'lifting' operator that preserves guarantees, as well as the structural relation to induced functions (Appx. A.2).

Note that our algorithm is exact: it returns a true minimizer of the empirical 0/1 loss. For many learning problems, this is known to be NP-hard—even for the canonical problem of linear classification [25]. Fortunately, the structure of our problems permits tractable solutions, and our algorithm is such.

Lemma 4.8. *ALG runs in $O((m\binom{n}{k})^2)$ time.*

Proof in Appx. E. This runtime is made possible due to several key factors: (i) only k-sized weights need to be learned, (ii) all weights are binary-valued, and (iii) loss queries are efficient in induced space. Nonetheless, when n and k are large, runtime may be significant, and so k must be chosen with care. Fortunately, our results in Sec. 5.1.1 give encouraging evidence that learning with small k—even $k = 1$, for which runtime is $O((mn)^2)$—is quite powerful.

In the analysis, the $m\binom{n}{k}$ is made possible only since weights are sparse, and since the algorithm operates on a finite sample set of size m. Alternatively, if m is large, then this expression can be replaced with $\binom{q}{k}$. This turns out to be necessary; in Appx. A.3 we show that, in the limit, $\binom{q}{k}$ is a lower bound.

5 BALANCE OF POWER

Our final section explores the question: what determines the balance of power between system and users? We begin with the perspective of the user, who has commitment power, but only sample-access to data. For her, the choice of complexity class k is key in balancing approximation error—how well (in principle) can functions $h \in H_k$ approximate v; and estimation error—how close the empirical payoff of the learned $\hat{h}$ is to its expected value. Our results give insight into how these types of error trade off as k is varied.

For the system, the important factors are k_1 and k_2, since these determine its flexibility in choosing representations. Since more feasible representation mean more flexibility, it would seem plausible that smaller k_1 and larger k_2 should help the system more. However, our results indicate differently: for system, *smaller* k_2 is better, and the choice of k_1 has limited effect on strategic users. The result for k_2 goes through a connection to the user's choice of k; surprisingly, smaller k turns out to be, in some sense, better for all.

5.1 User's perspective

We begin by studying the effects of k on user payoff. Recall that users aim to minimize the expected error (Eq. (4)):

$$\varepsilon(h) = \mathbb{E}_D[\mathbb{1}\{h(\phi_h(x)) \neq \text{sign}(v(x))\}],$$

but instead minimize the empirical error (Eq. (5)). For reasoning about the expected error of the learned choice function $\hat{h} \in H_k$,

a common approach is to decompose it into two error types—*approximation* and *estimation*:

$$\varepsilon(\hat{h}) = \underbrace{\varepsilon(h^*)}_{\text{approx.}} + \underbrace{\varepsilon(\hat{h}) - \varepsilon(h^*)}_{\text{estimation}}, \qquad h^* = \operatorname*{argmin}_{h' \in H_k} \varepsilon(h')$$

Approximation error describes the lowest error obtainable by functions in H_k; this measures the 'expressivity' of H_k, and is independent of $\hat{h}$. For approximation error, we define a matching complexity structure for value functions v, and give several results relating the choice of k and the complexity of v. Estimation error describes how far the learned $\hat{h}$ is from the optimal $h^* \in H_k$, and depends on the data size, m. Here we give a generalization bound based on VC analysis.

5.1.1 User approximation error. To analyze the approximation error, we must be able to relate choice functions h (that operate on representations z) to the target value function v (which operates on items x). To connect the two, we will again use induced functions, for which we now define a matching complexity structure.

Definition 5.1. A function $f : \mathcal{X} \to \{\pm 1\}$ has an *induced complexity* of ℓ if exists a function $g : \mathcal{Z}_\ell \to \{\pm 1\}$ s.t.:

$$f(x) = \begin{cases} 1 & \text{if } \exists z \subseteq x, |z| = \ell \text{ and } g(z) = 1 \\ -1 & \text{o.w.} \end{cases}$$

and ℓ is minimal (i.e., there is no such $g' : Z_{\ell-1} \to \{\pm 1\}$).

We show in Lem. 5.2 and Cor. 5.3 that the induced complexity of a function f captures the minimum $k \in [1, n]$ such that f is an induced function of an $h \in H_k$.

Lemma 5.2. *Let $k \leq k_2$. Then for every $h \in H_k$, the induced complexity of the corresponding f_h is $\ell \leq k$.*

Corollary 5.3. *Let $F_k = F_{H_k}$ be the induced function class of H_k, as defined in Def. 4.5. Then:*

$$F_k = \{f : \mathcal{X} \to \{\pm 1\} \ : \ f \text{ has induced complexity } \leq k\}$$

Proofs in Appx. F. We can now turn to considering the effect of k on approximation error. Since the 'worthwhileness' function $y(x) = \text{sign}(v(x))$ operates on x, we can consider its induced complexity, which we denote by ℓ^* (i.e., $y \in F_{\ell^*}$). The following result shows that if $\ell^* \leq k$, then H_k is expressive enough to perfectly recover y.

Theorem 5.4. *If $\ell^* \leq k$ then the approximation error is* 0.

Proof. Since the induced complexity of v is ℓ^*, there is a function $g : \mathcal{Z}_{\ell^*} \to \{\pm 1\}$ s.t.:

$$v(x) = \begin{cases} 1 & \text{if } \exists z \subseteq x, |z| = \ell^* \text{ and } g(z) = 1 \\ -1 & \text{o.w.} \end{cases}$$

Let $a_+ > \sum_{i \in [1,k]} \binom{n}{i}$ and $a_- \in (0, 1)$, and define the weight function w on k size subsets as follows: $w(z) = a_+$ if there exists a $z' \subseteq z$ such that $g(z') = 1$, and otherwise $w(z) = a_-$. We define h using w as follows:

$$h(z) = \text{sign}\left(\sum_{z' \in \Gamma_k(z)} w(z')\right)$$

We now show that for each $x \in \mathcal{X}$, $h(\phi_h(x)) = f_h(x) = v(x)$ implying $h_k^* = h$. Suppose $f_h(x) = 1$ for an $x \in \mathcal{X}$. Then there exists a $z \in \mathcal{Z}$ such that $z \subset x$ and $h(z) = 1$. From Theorem 4.6, and the choice of a_+ and a_- we have that there exists a $z \subset x$, $|z| = k$ such that $w(z) = a_+$. From the construction of w this implies there exists a $z \subset x$, $|z| = \ell^*$ such that $g(z) = a_+$. But then from the above definition of v this implies $v(x) = 1$. Similarly, we can argue, if $f_h(x) = -1$ then $v(x) = -1$ for any $x \in \mathcal{X}$. Hence, $h(\phi_h(x)) = v(x)$ for each $x \in \mathcal{X}$ implying $h_k^* = h$. Further, $U(h_k^*) = 1$ implying zero approximation error. □

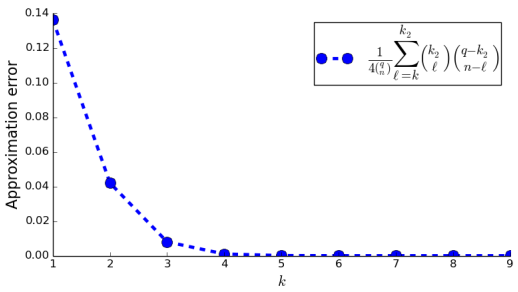

Figure 1: Upper bound on approximation error showing diminishing returns. Parameters: $q = 400, n = 30$ and $k_2 = 10$.

One conclusion from Thm. 5.4 is that if the user knows ℓ^*, then zero error is, in principle, obtainable; another is that there is no reason to choose $k > \ell^*$. In practice, knowing ℓ^* can aid the user in tuning k according to computational (Sec. 4.3) and statistical considerations (Sec. 5.1.2) Further conclusions relate ℓ^* and k_2:

Corollary 5.5. *If $\ell^* \leq k_2$ and the distribution D has full support on $\mathcal{X}$, then $k = \ell^*$ is the smallest k that gives zero approximation error.*

Corollary 5.6. *If $\ell^* > k2$, then the approximation error weakly increases with k, i.e., $H_k \leq H_{k-1}$ for all $k \leq k_2$. Furthermore, if the distribution D has full support on $\mathcal{X}$ then no k can achieve zero approximation error.*

In general, Corr. 5.6 guarantees only weak improvement with k. Next, we show that increasing k can exhibit clear diminishing-returns behavior, with most of the gain obtained at very low k.

Lemma 5.7. *Let D be the uniform distribution over $\mathcal{X}$. Then there is value function v for which $\varepsilon(h_k^*)$ diminishes convexly with k.*

The proof is constructive and given in Appx. A.4. We construct a v such that approximation error $h_k^* \in H_k$ is upper bounded by

$$\varepsilon(h_k^*) \leq \frac{1}{4\binom{q}{n}} \sum_{\ell=k}^{k_2} \binom{k_2}{\ell}\binom{q-k_2}{n-\ell}.$$

The diminishing returns property of upper bound is illustrated in Fig. 1. Although Lem. 5.7 describes a special case, we conjecture that the phenomena of diminishing returns applies more broadly.

The second results shows that learning k_1-order functions can be as powerful as learning subadditive functions (Appx. A.5); hence, learning with $k = k_1$ is highly expressive. Interestingly, the connection between general (k-order) functions and class of subadditive functions is due to the strategic response mapping, ϕ.

Lemma 5.8. *Consider threshold-subadditive functions:*

$$H_{\mathrm{SA}} = \{\mathrm{sign}(g(z)) \,:\, g \text{ is subadditive on subsets in } \mathcal{Z}\}$$

Then for every threshold-subadditive $h_g \in H_{\mathrm{SA}}$, there is an $h \in H_{k_1}$ for which $h(\phi_h(x)) = h_g(\phi_{h_g}(x))\ \forall x \in \mathcal{X}$.

5.1.2 User estimation error. For estimation error, we give generalization bounds based on VC analysis. The challenge in analyzing functions in H_k is that generalization applies to the *strategic* 0/1 loss, i.e., $\mathbb{1}\{h(\phi_h(x)) \neq y\}$, and so standard bounds (which apply to the standard 0/1 loss) do not hold. To get around this, our approach relies on directly analyzing the VC dimension of the induced class, F_k (a similar approach was taken in Sundaram et al. [26] for SC). This allows us to employ tools from VC theory, which give the following bound.

Theorem 5.9. *For any k and m, given a sample set S of size m sampled from D and labeled by some v, Algorithm returns an $\hat{h} \in H_k$ for which it holds that:*

$$\varepsilon(\hat{h}) - \varepsilon(h_k^*) \leq \sqrt{\frac{C(\binom{q}{k}\log(\binom{q}{k}/\epsilon) + \log(1/\delta)}{m}}$$

w.p. at least $1-\delta$ over S, and for a fixed constant C.

Proof. We first argue that the VC dimension of H_k is at most $\binom{n}{k}$. Let $d = \sum_{i\in[1,k]}\binom{n}{i}$, index the vectors in $\{0,1\}^d$ by $z \subset E$ (the ground set), such that $|z| \leq k$. Then each $z \in \mathcal{Z}$ can be represented by a binary vector $e_z \in \{0,1\}^d$, with the entry indexed by a z' being 1 if and only if $z' \subseteq z$. Further, let $w \in \{a_-, a_+\}^d$ be a binary weighted vector with a_- and a_+ as in Def. 4.3. Then from the definition of H_k, for each $h \in H_k$, there is a $w_h \in \{a_-, a_+\}^d$ such that a)$h(z) = \mathrm{sign}(\langle w, e_z\rangle)$ for all $z \in Z$, and b) the entry of w indexed by a z' with $|z'| < k$ is a_-. From this we observe that the VC dimension of H_k is at most $\binom{n}{k}$, since each $h \in H_k$ is decided by the realization of binary weights on entries indexed by the $\binom{n}{k}$ sets. Since Alg minimizes the empirical error (Theorem 4.7), the theorem follows by noting that the bound in the theorem statement is the agnostic PAC generalization guarantee for an algorithm minimizing the empirical error in the standard classification setting with VC dimension at most $\binom{n}{k}$. □

The proof relies on Thm. 4.6; since h and f_h share weights, the induced F_k can be analyzed as a class of q-variate degree-k multilinear polynomials. Since induced functions already incorporate ϕ, VC analysis for the 0/1 loss can be applied. Note that such polynomials have exactly $\binom{q}{k}$ degrees of freedom; hence the term in the bound.

5.2 System's perspective

The system's expressive power derives from its flexibility in choosing representations z for items x. Since k_1, k_2 determine which representations are feasible, they directly control the system's power to manipulate; and while the system itself may not have direct control over k_1, k_2 (i.e., if they are set by exogenous factors like screen size), their values certainly affect the system's ability to optimize engagement. Our next result is therefore unintuitive: for system, a smaller k_2 is better (in the worst case), even though it reduces the set of feasible representations. This result is obtained indirectly, by considering the effect of k_2 on the user's choice of k.

Lemma 5.10. *There exists a distribution D and a value function v such that for all $k < k' \leq k_2$, system has higher payoff against the optimal $h_k^* \in H_k$ than against $h_{k'}^* \in H_{k'}$.*

The proof is in Appx. F; it uses the uniform distribution, and the value function from Thm. 5.7. Recalling that the choice of k controls the induced complexity ℓ (Corr. 5.3), and that users should choose k to be no greater than k_2, we can conclude the following:

Corollary 5.11. *For the system, lower k_2 is better (in a worst-case sense).*

For k_1, it turns out that against strategic users, it is entirely inconsequential. The reason is that payoff to the strategic user is derived entirely from k—which is upper-bounded by k_2, but can be set lower than k_1. This invariance is derived immediately from how functions in H_k are defined, namely that $w(z) = a_-$ for all z with $|z| < k$ (Def. 4.3). This, however, holds when the strategic user chooses to learn over H_k for some k. Consider, alternatively, a strategic user that decides to learn subadditive functions instead. In this case, Thm. 5.8 shows that k_1 determines the users 'effective' k; the smaller k_1, the smaller the subset of subadditive functions that can be learned. Hence, for user, smaller k_1 means worse approximation error. This becomes even more pronounced when facing a naïve user; for her, a lower k_1 means that system now has a large set of representations to choose from; if even one of them has $v(z) = 1$, the system can exploit this to increase its gains. In this sense, as k_1 decreases, payoff to the system (weakly) improves.

6 DISCUSSION

Our analysis of the balance of power reveals a surprising conclusion: for both parties, in some sense, simple choice functions are better. For system, lower k improves its payoff through how it relates to k_2 (Corr. 5.11). For users, lower k is clearly better in terms of runtime (Lem. 4.8) and estimation error (Thm. 5.9), and for approximation error, lower k has certain benefits—as it relates to ℓ^* (Corr. 5.5), and via diminishing returns (Thm. 5.7). Thus, and despite their conflicting interests—to some degree, the incentives of the system and its users align.

But the story is more complex. For users, there is no definitive notion of 'better'; strategic users always face a trade-off, and must choose k to balance approximation, estimation, and runtime. In principle, users are free to choose k at will; but since there is no use for $k > k_2$, a system controlling k_2 de facto controls k as well. This places a concrete restriction on the freedom of users to choose, and inequitably: for small k_2, users whose v has complexity $\leq k_2$ (i.e., having 'simple tastes') are less susceptible to manipulation than users with v of complexity $> k_2$ (e.g., fringe users with eclectic tastes) (Thm. 5.4, Corrs. 5.5, 5.6). In this sense, the choice of k_2 also has implications on fairness. We leave the further study of these aspects of strategic representation for future work.

From a purely utilitarian point of view, it is tempting to conclude that systems should always set k_2 to be low. But this misses the broader picture: although systems profit from engagement, users engage only if they believe it is worthwhile to them, and dissatisfied users may choose to leave the system entirely (possibly into the hands of another). Thus, the system should not blindly act to maximize engagement; in reality, it, too, faces a tradeoff.

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A ADDITIONAL RESULTS

A.1 Agnostic User

Theorem A.1 stated below is the formal version of Theorem 3.2 in Section 3. Theorem A.1 shows that given a a large enough sample size m, an agnostic user's payoff would approach $\max\{\mu, 1-\mu\}$, where $\mu = \mathbb{E}_D[y]$.

Theorem A.1. *Let $\frac{2}{2+\sqrt{m}} \leq \delta < 1/8$ and $\tau = \frac{\delta}{2(1-\delta)} + \sqrt{\frac{2\log(1/\delta)}{m}}$, then agnostic user's expected payoff guarantee is given by*

$$\begin{cases} \geq (1-\delta)(1-\mu) & \text{if } \widehat{\mu} \leq 1/2 - \tau \\ \geq (1-\delta)\mu & \text{if } \widehat{\mu} \geq 1/2 + \tau \\ = 1/2 & \text{Otherwise} \end{cases}$$

Before we prove the theorem, we state Hoeffeding's inequality, which is a well known result from probability theory.

Lemma A.2. *Let $S_m = \sum_{i=1}^{m} X_i$ be the sum of m i.i.d. random variables with $X_i \in [0,1]$ and $\mu = \mathbb{E}[X_i]$ for all $i \in [m]$, then*

$$\mathbb{P}\left(\frac{S_m}{m} - \mu \geq \varepsilon\right) \leq e^{-2m\varepsilon^2} \quad \text{and,} \quad \mathbb{P}\left(\frac{S_m}{m} - \mu \leq -\varepsilon\right) \leq e^{-2m\varepsilon^2}.$$

We will use the following equivalent form of the above inequality. Let $\delta := e^{-2m\varepsilon^2}$ i.e. $\varepsilon = \sqrt{\frac{2\log(1/\delta)}{m}}$ and $\widehat{\mu} = \frac{S_m}{m}$. Then we have with probability at-least $(1-\delta)$ we have

$$\mu \leq \widehat{\mu} + \sqrt{\frac{2\log(1/\delta)}{m}} \text{ and,} \tag{6}$$

$$\mu \geq \widehat{\mu} - \sqrt{\frac{2\log(1/\delta)}{m}} \tag{7}$$

Now we are ready to give the proof of Theorem A.1

Proof of Theorem A.1. We begin with the following supporting lemma.

Lemma A.3. *Let $\frac{2}{2+\sqrt{m}} \leq \delta < 1/8$, then $\tau < 1/2$.*

Proof. The proof follows from following sequence of inequalities,

$$\frac{2}{2+\sqrt{m}} < \delta \iff m > 4(1/\delta - 1)^2 \implies m > 4(1/\delta - 1)\log(1/\delta) \iff \frac{\delta}{2(1-\delta)} > \frac{2\log(1/\delta)}{m}$$

Let $\gamma = \frac{\delta}{2(1-\delta)}$. We have $\tau = \gamma + \sqrt{\gamma}$ which is an increasing function of δ, so we the maximum is achieved at $\delta = 1/8$ and is given by $1/\sqrt{14} + 1/14 < 1/2$. This completes the proof of the lemma. □

From, lemma A.3 we have that $1/2 + \tau < 1$, hence there is a non-trivial range i.e. $\widehat{\mu} \in [1/2+\tau, 1]$ where user assigns $h(z) = +1$ for all z with probability 1. Similarly, when $\widehat{\mu} \in [0, 1/2-\tau]$ user assigns $h(z) = -1$ for all z with probability 1. We will consider three cases separately.

Case 1 ($\widehat{\mu} \in [1/2+\tau, 1]$): From Hoeffding's inequality (Eq. 7) we have that with probability at-least $(1-\delta)$,

$$\mu \geq \widehat{\mu} - \sqrt{\frac{2\log(1/\delta)}{m}}$$
$$\implies \mu \geq 1/2 + \frac{\delta}{2(1-\delta)} = \frac{1}{2(1-\delta)}$$

Hence, with probability at-least $(1-\delta)$ an agnostic user will get a payoff of μ. Hence, the expected payoff in this case is at-least $(1-\delta)\mu \geq 1/2 \geq (1-\delta)(1-\mu)$.

Case 2 ($\widehat{\mu} \in [0, 1/2-\tau]$): Similar to Case 1 here we use tail bound given by Hoeffding's inequality (Eq. 6) to get with probability at-least $(1-\delta)$,

$$\mu \leq \widehat{\mu} + \sqrt{\frac{2\log(1/\delta)}{m}}$$
$$\implies \mu \leq 1/2 - \frac{\delta}{2(1-\delta)} = \frac{1-2\delta}{2(1-\delta)}$$

Hence, $(1-\mu) \geq \frac{1}{2(1-\delta)}$. The agnostic user guarantees for the payoff of $(1-\mu)$ with probability at-least $(1-\delta)$ in this case. Hence we have the payoff of $(1-\delta)(1-\mu) \geq 1/2 \geq (1-\delta)\mu$ in this case.

Case 3 ($\widehat{\mu} \in (1/2-\tau, 1/2+\tau)$): Finally, in this case, the agnostic user chooses $h(z) = 1$ for all $z \in \mathcal{Z}$ with probability $1/2$ and $h(z) = -1$ for all $z \in \mathcal{Z}$ with probability $1/2$. Hence, the expected payoff is given by $\frac{1}{2}\mu + \frac{1}{2}(1-\mu) = 1/2$ irrespective of the true mean μ of positive samples. □

A.2 Lifted functions

The relation between choice functions and their induced counterparts passes through an additional type of functions that operate on sets of size *exactly* ℓ. Denote $\mathcal{Z}_\ell = \{z \in \mathcal{Z} : |z| = \ell\}$, and note that all feasible representations can be partitioned as $\mathcal{Z} = \mathcal{Z}_{k_1} \uplus \ldots \uplus \mathcal{Z}_{k_2}$. We refer to functions that operate on single-sized sets as *restricted functions*. Our next result shows that choice functions in H_k can be represented by restricted functions over $\mathcal{Z}_k$ that are 'lifted' to operate on the entire $\mathcal{Z}$ space. This will allow us to work only with sets of size exactly k.

Lemma A.4. *For each $h \in H_k$ there exists a corresponding $g : Z_k \to \{\pm 1\}$ such that $h = lift(g)$, where:*

$$lift(g)(z) = \begin{cases} 1 & \text{if } k \le |z| \text{ and} \\ & \exists z' \subseteq z, |z'| = k \text{ s.t. } g(z') = 1 \\ -1 & \text{o.w.} \end{cases}$$

Proof. Let $h \in H_k$. Then there is a weight function w on sets of size at most k such that either $w(z) \in (-1, 0)$ or $w(z) > \sum_{i\in[k]} \binom{n}{i}$, and

$$h(z) = \text{sign}\left(\sum_{z':z'\subseteq z, |z'|\le k} w(z')\right)$$

Define $g : \mathcal{Z}_k \to \{-1, 1\}$ such that for a $z \in \mathcal{Z}_k$, $g(z) = 1$ if $w(z) > 0$ and $g(z) = -1$ otherwise. It is easy to see from the choice of $w(z)$ that $h = lift(g)$. □

A.3 Runtime Lower Bound

As given in Lemma 4.8, the runtime of our algorithm is $m(\binom{n}{k})^2$. We argued in Section 4 that is made possible only since weights are sparse, and since the algorithm operates on a finite sample set of size m. If m is large, then this expression can be replaced with $\binom{q}{k}^2$. We now show that, in the limit (or under full information), the dependence on $\binom{q}{k}$ is necessary. The conclusion from Lemma A.5 is that to find the loss minimizer, any algorithm must traverse at least all such h; since there exist $\binom{q}{k}$ such functions, this is a lower bound. This is unsurprising; H_k is tightly related to the class of multilinear polynomials, whose degrees of freedom are exactly $\binom{q}{k}$.

Lemma A.5. *Consider a subclass of H_k composed of all h who have $w(z) = a_+$ for exactly one z with $|z| = k$, and $w(z) = a_-$ otherwise. Then, for every such h, there exists a corresponding v, such that h is a unique minimizer (within this subclass) of the error w.r.t. v.*

Proof. Let z_1 and z_2 be distinct k size subsets, and let $a_- \in (0, 1)$ and $a_+ > \sum_{i\in[1,k]} \binom{n}{i}$. Further, let w_i, $i \in [1, 2]$ be a weight function that assigns a_+ to z_i and a_- to all other subsets of size at most k. Let h_1 and h_2 be two function in H_k defined by the binary weighted functions w_1 and w_2 respectively. It is easy to see that for $v_i = f_{h_i}$ the approximation error (see (Eq. (4))) of h_i is zero. Hence, to prove the lemma it is sufficient to show that $f_{h_1} \neq f_{h_2}$.

Suppose $f_{h_1} = f_{h_2}$. Since $z_1 \neq z_2$, there exists an $x \in \mathcal{X}$ such that $z_1 \subseteq x$ but $z_2 \subseteq x$. From Theorem 4.6 and the choice of a_+ and a_-, this implies $f_{h_1}(x) = 1$ but $f_{h_2}(x) = -1$, and hence, a contradiction. □

A.4 Diminishing Returns

In this section, we demonstrate via an example that increasing k can exhibit clear diminishing-returns behavior, with most of the gain obtained at very low k. The error function decreases for the v constructed in Lemma 5.7 as shown in Figure 1 for $q = 400$, $n = 30$, and $k_2 = 10$. The horizontal axis corresponds to k (the complexity of the learning class), and the vertical access corresponds to error of the optimal choice function from the hypothesis class. Although Lem. 5.7 describes a special case, we conjecture that the phenomena of diminishing returns applies more broadly.

Lemma 5.7. *Let D be the uniform distribution over $\mathcal{X}$. Then there is value function v for which $\varepsilon(h_k^*)$ diminishes convexly with k.*

Proof. We construct a v such that approximation error $h_k^* \in H_k$ is as given below

$$\varepsilon(h_k^*) \le \frac{1}{4\binom{q}{n}} \sum_{\ell=k}^{k_2} \binom{k_2}{\ell}\binom{q-k_2}{n-\ell}.$$

It is easy to see that $\varepsilon(h_k^*)$ diminishes convexly with k (see Fig. 1). We choose k_2 elements $e_1, e_2, \ldots, e_{k_2} \in E$ (the ground set), and let z_e be the k_2 size subset consisting of these k_2 elements. For a $v : \mathcal{X} \to \mathbb{R}$, let $\mathcal{X}_v^+ = \{x \in \mathcal{X} | \text{ sign}(v(x)) = 1\}$ and $\mathcal{X}_v^- = \{x \in \mathcal{X} | \text{ sign}(v(x)) = -1\}$. We first show that there exists a v with the following two properties:

(1) if $x \in \mathcal{X}_v^+$ then there exists a $z \subseteq z_e$ such that $z \subset x$.
(2) For $k \in [1, k_2]$, let $\mathcal{X}_k = \{x \in \mathcal{X} | \exists z \subseteq z_e, |z_e| = k, \text{ and } z_e \subset x\}$. Then $\mathcal{X}_v^+ \cap \mathcal{X}_k = \frac{3}{4}(\sum_{\ell=k}^{k_2} \binom{k_2}{\ell}\binom{q-k_2}{n-\ell})$, for every $k \in [1, k_2]$.
(3) For every $z \subset z_e$, let $\mathcal{X}_z = \{x \in \mathcal{X} \mid z \subset x\}$. Then $|\mathcal{X}_v^+ \cap \mathcal{X}_z| = \frac{3}{4}\binom{q-k}{n-k}$, where $|z| = k$.

We construct such a v iteratively. We begin by making the following observation.

Observation A.6. *For each $k \in [1, k_2]$, $|\mathcal{X}_k| = \sum_{\ell=k}^{k_2} \binom{k_2}{\ell}\binom{q-k_2}{n-\ell}$.*

Proof. Recall $\mathcal{X}$ consists of size n subsets of E. For a $k \in [1, k_2]$ we wish to choose n size subsets of E that contain a $z \subseteq z_e$. This equivalent to choosing a fixed $\ell \geq k$ size subset of z_e and then choosing the remaining $n - \ell$ elements from the $q - k_2$ elements (not part of z_e) in E. For every $\ell \geq k$ we can choose ℓ size subset of z_e in $\binom{k_2}{\ell}$ ways, and for each such choice we can choose the remaining $n - \ell$ elements in $\binom{q-k_2}{n-\ell}$ ways. Since, this holds for any $\ell \in [k, k_2]$, we have $|\mathcal{X}_k| = \sum_{\ell=k}^{k_2} \binom{k_2}{\ell}\binom{q-k_2}{n-\ell}$. □

Constructing v: The idea is to iteratively add elements in $\mathcal{X}$ to $\mathcal{X}_v^+$, that is, iteratively determine the $x \in \mathcal{X}$ such that $\text{sign}(v(x)) = 1$. In the first round, we arbitrarily choose $\frac{3}{4}\binom{q-k_2}{n-k_2}$ from $\mathcal{X}_{k_2}$ and add it to $\mathcal{X}_v^+$, and the remaining $\frac{1}{4}\binom{q-k_2}{n-k_2}$ are added to $\mathcal{X}_v^-$. At round k, assume we have constructed a v satisfying the above three properties for $k' > k$, that is,

(1) if $x \in \mathcal{X}_v^+$ then there exists a $z \subseteq z_e$ such that $|z| > k$ and $z \subset x$.
(2) $\mathcal{X}_v^+ \cap \mathcal{X}_{k'} = \frac{3}{4}(\sum_{\ell=k'}^{k_2} \binom{k_2}{\ell}\binom{q-k_2}{n-\ell})$, for every $k' \in [k+1, k_2]$.
(3) For every $z \subset z_e$, let $\mathcal{X}_z = \{x \in \mathcal{X} \mid z \subset x\}$. Then $|\mathcal{X}_v^+ \cap \mathcal{X}_z| = \frac{3}{4}\binom{q-k'}{n-k'}$, where $|z| = k' > k$.

Hence, at round k, we have $\binom{k_2}{k}\binom{q-k_2}{n-k}$ elements in $\mathcal{X}_k$ elements in $\mathcal{X}$ that contain a k size subset of z_e. From these elements in $\mathcal{X}_k$, for every k size subset $z \subset z_e$ we arbitrarily choose $\frac{3}{4}\binom{q-k_2}{n-k}$ elements containing z and add the remaining $\frac{1}{4}\binom{q-k_2}{n-k}$ elements to $\mathcal{X}_v - 1$. It is easy to verify that v satisfies the first two properties for every $k' \in [k, k_2]$ after this procedure. Now we argue v satisfies the third property for any $z \subset z_e$, such that $|z| = k$. The n size sets in $\mathcal{X}$ containing a $z \subset z_e$, such that $|z| = k$, can be partitioned into sets containing different $\ell >= k$ size subsets of z_e. In particular, we have the following combinatorial equality

$$\binom{q-k'}{n-k'} = \sum_{\ell=k'}^{k_2} \binom{k_2-k'}{\ell-k'}\binom{q-k_2}{n-\ell}$$

In the above expression, $\binom{q-k_2}{n-\ell}$ corresponds to the number of n size sets that contain only a a specific $\ell \geq k'$ size subset of z_e. Since our iterative procedure ensures from each such partition at least $\frac{3}{4}$ fraction of x is added to $\mathcal{X}_v^+$, we have that v satisfies the third property.

Optimal $h^* \in H_k$: From the construction of v, it is clear that the optimal $h^* \in H_k$ for the above constructed v, for any $k \in [1, k_2]$ satisfies the following: for every $z \in \mathcal{Z}$, $h^*(z) = 1$ if and only if there exists a $z' \subseteq z_e$, $|z'| = k$, and $z' \subseteq z$. Further as D is the uniform distribution, for such an h^*:

$$\varepsilon(h_k^*) \leq \frac{1}{4\binom{q}{n}} \sum_{\ell=k}^{k_2} \binom{k_2}{\ell}\binom{q-k_2}{n-\ell}.$$

□

A.5 Relation to Subadditive Functions

We conclude this section by showing that, for learning, k_1-order functions can be as powerful as subadditive functions.

Lemma 5.8. *Consider threshold-subadditive functions:*

$$H_{\text{SA}} = \{\text{sign}(g(z)) \ : \ g \text{ is subadditive on subsets in } \mathcal{Z}\}$$

Then for every threshold-subadditive $h_g \in H_{\text{SA}}$, there is an $h \in H_{k_1}$ for which $h(\phi_h(x)) = h_g(\phi_{h_g}(x)) \ \forall x \in \mathcal{X}$.

Proof. Let $h \in H_{\text{SA}}$ with a corresponding $g : \mathcal{Z} \to \mathbb{R}$ such that $h(z) = \text{sign}(g(z))$ for all $z \in \mathcal{Z}$. Choose an $a_+ > \sum_{i=1}^{k_1} \binom{n}{i}$, and $a_- \in (0, 1)$. Define a weight function w on size at most k_1 sets as follows:

$$w(z) = \begin{cases} a_+ & \text{if } |z| = k_1,\ h(z) = 1 \\ a_- & \text{o.w.} \end{cases}$$

Let $h' \in H_{k_1}$ be the function defined by the binary weight w as defined above. We argue that for every $x \in \mathcal{X}$, if $h(\phi_h(x)) = h'(\phi_{h'}(x))$. For every $x \in \mathcal{X}$, $h(\phi_h(x)) = 1$ if and only if there is a $z \in \mathcal{Z}$ and $z \subseteq x$ such that $h(z) = 1$. Since g is sub-additive, this implies $h(\phi_h(x)) = 1$ if and only if there is a $z \subseteq x$ such that $|z| = k_1$ and $h(z) = 1$, and hence $w(z) = a_+$. From Theorem 4.6 this implies, $h(\phi_h(x)) = 1$ if and only if $h'(\phi_{h'}(x)) = 1$. □

B ADDITIONAL RELATED WORK

Hierarchies of set functions. Conitzer et al. [7] (and independently, Chevaleyre et al. [6]) suggest a notion of k-wise dependent valuations, to which our Definition 4.1 is related. We also allow up to k-wise dependencies, but our valuations need not be positive and we focus on their sign (an indication whether an item is acceptable or not). Our set function valuations are also over item attributes rather than multiple items. Despite the differences, the definitions have a shared motivation: Conitzer et al. [7] believe that this type of valuation is likely to arise in many economic scenarios, especially since due to cognitive limitations, it might be difficult for a player to understand the inter-relationships between a large group of items. Hierarchies of valuations with limited dependencies/synergies have been further studied by Abraham et al. [2], Feige et al. [10] under the title 'hypergraph valuations'. These works focus on monotone valuations that have only positive weights for

every subset, and are thus mathematically different than ours.

Learning set functions. Concept learning refers to learning a binary function over hypercubes [3] through a query access model. Abboud et al. [1] provide a lower bound on *membership queries* to exactly learn a threshold function over sets where each element has small integer valued weights. Our learning framework admits large weights and has only a sample access in contrast with the query access studied in this literature. Feldman [11] show that this problem is computationally hard to learn with sample access. A by-now classic work in learning theory studies the learnability from data of submodular (non-threshold) set functions [4]. Though we consider learning subadditive functions in this work, an extension to submodular valuations is a natural extension. Learning set functions is in general hard, even for certain subcalsses such as submodular functions. Rosenfeld et al. [24] show that it's possible to learn certain parameterized subclasses of submodular functions, when the goal is to use them for optimization. But this refers to learning over approximate proxy losses; whereas in our work, we show that learning is possible directly over the 0/1 loss.

C MISSING PROOF FROM SECTION 2

Observation 2.1. *In a strategic representation game, every best-response $z \in \phi_h(x)$ induces the same expected payoff to the user.*

Proof. The proof follows from the definition of best response (Eq. 3). Let $z_1, z_2 \in \phi_h(x)$. Then since ϕ_h consists of only best response, we have either $h(z_1) = h(z_2) = 1$, or $h(z_1) = h(z_2) = -1$. Hence, $h(z_1) = \text{sign}(v(x))$ if and only if $h(z_2) = \text{sign}(v(x))$ for any $z_1, z_2 \in \phi_h(x)$. □

D MISSING PROOF FROM SECTION 3 AND AN ADDITIONAL EXAMPLE

D.1 Naïve users and Benevolent system

Lemma 3.1. *If system plays the* benevolent *strategy:*

$$\phi_h^{\text{benev}}(x) = \underset{z \subseteq x, |z| \in [k_1, k2]}{\text{argmax}} \{\mathbb{1}\{h(z) = \text{sign}(v(x))\},$$

then the naïve approach maximizes user payoff.

Proof. Since a naïve user plays $h(z) = \text{sign}(v(z))$, for each $x \in \mathcal{X}$ the payoff of the user is maximized if in response the system plays a $z \subseteq x$ such that $\text{sign}(v(z)) = \text{sign}(v(x))$. Observe that, if there exists a $z \in \mathcal{Z}$ and $z \subseteq x$, such that $\text{sign}(v(z)) = \text{sign}(v(x))$ then $z \in \phi_h^{\text{benev}}(x)$ and consequently the user's payoff is maximized for such an x. Conversely, if there exists no $z \in \mathcal{Z}$ and $z \subseteq x$, such that $\text{sign}(v(z)) = \text{sign}(v(x))$, then no truthful system can ensure more than zero utility for such a x. Hence, a benevolent system maximizes the utility of a naïve user. □

Now, we present an additional example to show how a naïve users choice function can be manipulated by the strategic system and as a consequence, user may obtain arbitrarily small payoff against a strategic system.

Example 2. Let $x_1 = \{a_1, a_2\}, x_2 = \{a_1, a_3\}, x_3 = \{a_1, a_4\}, x_4 = \{a_2, a_3\}, x_5 = \{a_3, a_4\}\}$ with $\text{sign}(v(x_1)) = \text{sign}(v(x_5)) = \text{sign}(v(a_2)) = \text{sign}(v(a_4)) = +1$ and $\text{sign}(v(x_2)) = \text{sign}(v(x_3)) = \text{sign}(v(x_4)) = \text{sign}(v(a_1)) = \text{sign}(v(a_3)) = -1$. Further, let $k_1 = k_2 = 1$ with $z_i = a_i$ as representations and a distribution $D = (\frac{\varepsilon}{4}, \frac{\varepsilon}{4}, 1-\varepsilon, \frac{\varepsilon}{4}, \frac{\varepsilon}{4})$ supported over $(x_1, x_2, x_3, x_4, x_5)$.

A unique truthful representation for this instance is $h = (-1, +1, -1, +1)$. A strategic agent can manipulate a naïve agent into non-preferred choices by using a representation $(a_2, a_1, a_4, a_2, a_4)$ for $(x_1, x_2, x_3, x_4, x_5)$. Note here that a naïve agent expected z_1 as a representation for x_3 since $h(z_1) = \text{sign}(v(x_3)) = -1$ and $h(z_4) = +1 \neq \text{sign}(v(x_3))$. However, a strategic agent chose a_4 as under given h we have $h(a_4) = 1$. A naïve users payoff in this case is reduced to ε which can be arbitrarily small.

E MISSING PROOFS FROM SECTION 4

Lemma 4.2. *For any $h : \mathcal{Z} \to \{\pm 1\}$, there exists a $k \leq k_2$ and a corresponding k-order function h' such that:*

$$h(\phi_h(x)) = h'(\phi_{h'}(x)) .$$

Proof. Let $k = \min_{k' \in [k_1, k_2]} \{\exists z$ such that $|z| = k$ and $h(z) = 1$, but for all $z' \subset z$ and $z \in \mathcal{Z}$ $h(z') = -1\}$. Define h' as follows: for $|z| < k$, $h'(z) = -1$, and for $|z| >= k$

$$h'(z) = 1 \ \exists z, |z| \leq k \text{ and } h(z) = 1$$

$$h'(z) = -1 \text{ otherwise}$$

First, we argue that h' defined as above satisfies $h'(\phi_{h'}(x)) = h(\phi_h(x))$ for all $x \in \mathcal{X}$. Suppose $h(\phi_h(x)) = 1$. Then there exist $z \in \mathcal{Z}$ such that $z \subset x$ and $h(z) = 1$. From the choice of k, we may assume without loss of generality that $|z| \leq k$. This implies there exists z' such that $z \subseteq z' \subset x$ such that $h'(z') = 1$, and hence $h'(\phi_{h'}(x)) = h(\phi_h(x)) = 1$. Now suppose $h(\phi_h(x)) = -1$. Then for all $z \subset x$ we have $h(z) = -1$. In particular, for all $z \subset x$ such that $|z| < k$ we have $h(z) = -1$. This implies for all $z \subset x$ such that $|z| \geq k$ we have $h'(z) = -1$. This is because if there exists $z \subset x$ such that $|z| \geq k$ and $h'(z) = 1$ then from the definition of h' there exists a $z' \subset z \subset x$ such that $|z'| < k$, and $h(z') = 1$ (a contradiction). Additionally, from definition, for all $z \subset x$ such that $|z| < k$ we have $h'(z) = -1$. Hence, if $h(\phi_h(x)) = -1$ then $h'(\phi_{h'}(x)) = -1$.

Now, we show that h' is an order k function. Let $w(z) = a_- < -1$ for all z such that $|z| < k$. Further, for all z such that $|z| = k$ and $h'(z) = 1$, let $w(z) = a_+ > \sum_{i\in[k]} \binom{n}{i}$. It is easily verified that

$$h'(z) = \text{sign}\left(\sum_{z':z'\subseteq z, |z'|\leq k} w(z')\right)$$

□

Lemma 4.8. *ALG runs in $O((m\binom{n}{k})^2)$ time.*

PROOF. In the first two for loops, for each $x \in S^+$ (or in S^-) the internal for loop runs for $O(\binom{n}{k})$. Also, $|V| < |Z_{k,S}| \leq m\binom{n}{k}$, so the while loop takes at most $O(m\binom{n}{k})$. Finally, the argmax operation in the first step, and the re-computation of $\mu(z)$ in the last step of the while loop are each $O(m\binom{n}{k})$ operations. This amounts to a total of $O((m\binom{n}{k})^2)$. □

E.1 Proof of Theorem 4.7

Throughout, for ease of notation, we use $x \in S$ to denote $x \in \{x_1, \ldots, x_m\}$. let $Z_k = \{z : |z| = k, \exists x \in S\ z \subseteq x\}$. Recall $Z_{k,S}$ is equal to Z_k at the beginning of the algorithm. Also, for each $z \in Z_k$, let $\mathcal{X}_z = \{x \in S \mid z \subset x\}$.

We begin by expressing for each $h \in H_k$ with binary weights w_h, the empirical error in terms of $z \in Z_k$, and this would reveal why ALG, minimizes the empirical error. We begin with a few definitions for an $h \in H_k$ with binary weights w_h. Let $Z_h^+ = \{z \in Z_k \mid w_h(z) = a_+\}$, and $Z_h^- = \{z \in Z_k \mid w_h(z) = a_-\}$. Further, let $\mathcal{X}_{h,S}^+ = \{x \in S \mid \exists z \in Z_h^+, z \subset x\}$, and $\mathcal{X}_{h,S}^- = \{x \in S \mid \forall z \in Z_k \text{ and } z \subset x, z \notin Z_h^+\}$. The proof of Lemma E.1 uses Theorem 4.6 to characterize the error for an $h \in H_k$.

Lemma E.1. *Let $h \in H_k$, and let the empirical error of h on set training set S be $e(h, S)$. Then*

$$\mu(h, S) = \left(\sum_{x\in\mathcal{X}_{h,S}^+} \hat{p}(x)\cdot y\right) - \left(\sum_{x\in\mathcal{X}_{h,S}^-} \hat{p}(x)\cdot y\right) = 1 - 2e(h, S)$$

PROOF. First, we rewrite the two terms in RHS of the expression of the lemma as follows:

$$\sum_{x\in\mathcal{X}_{h,S}^+} \hat{p}(x)\cdot y = \sum_{x\in\mathcal{X}_{h,S}^+} (\hat{p}(x)\mathbb{1}\{y=1\} - \hat{p}(x)\mathbb{1}\{y=-1\}) \tag{8}$$

$$-\sum_{x\in\mathcal{X}_{h,S}^-} \hat{p}(x)\cdot y = \sum_{x\in\mathcal{X}_{h,S}^-} (-\hat{p}(x)\mathbb{1}\{y=1\} + \hat{p}(x)\mathbb{1}\{y=-1\}) \tag{9}$$

Now, for every $x \in \mathcal{X}_{h,S}^+$, from Theorem 4.6, $h(\phi_h(x)) = 1$. Hence, for every $x \in \mathcal{X}_{h,S}^+$, if $y = -1$ then it contributes to error. Similarly, for every $x \in \mathcal{X}_{h,S}^-$, from Theorem 4.6 and definition of $\mathcal{X}_{h,S}^-$, we have $h(\phi_h(x)) = -1$. Hence, for every $x \in \mathcal{X}_{h,S}^-$, if $y = 1$ then it contributes to error. Hence,

$$\left(\sum_{x\in\mathcal{X}_{h,S}^+} \hat{p}(x)\mathbb{1}\{y=-1\}\right) + \left(\sum_{x\in\mathcal{X}_{h,S}^-} \hat{p}(x)\mathbb{1}\{y=1\}\right) = e(h, S)\,. \tag{10}$$

Similarly,

$$\left(\sum_{x\in\mathcal{X}_{h,S}^+} (\hat{p}(x)\mathbb{1}\{y=1\})\right) + \left(\sum_{x\in\mathcal{X}_{h,S}^-} \hat{p}(x)\mathbb{1}\{y=-1\}\right) = 1 - e(h, S)\,. \tag{11}$$

Adding the first two equations, and using the above two equations, we get the expression in the lemma. □

We will argue that our algorithm computes $\hat{h}$ that maximizes $\mu(h, S)$, and hence from Lemma E.1 minimizes the empirical error. First, we determine the sets $\mathcal{X}_{\hat{h},S}^+$ and $\mathcal{X}_{\hat{h},S}^-$. Let the while loop (steps 14-19) of the algorithm run for c times, and z_i^* be the element computed at line 15 in iteration $i \in [1, c]$. Now we make the following observation, which easily follows.

Observation E.2. *An $x \in \mathcal{X}_{\hat{h},S}^+$ if and only if either of the following is true: a) at step 5 (the second for loop), step 6 returns true, or b) $z_i^* \subset x$ for any $i \in [1, c]$. Further, for $x \in \mathcal{X}_{\hat{h},S}^+$ satisfying condition a, $v(x) = 1$.*

At step 15, since z_i^* maximizes $\mu(z)$, and the algorithm runs the while loop till there is $\mu(z) \geq 0$, we have from the above observation that $(\sum_{x\in\mathcal{X}_{\hat{h},S}^+} \hat{p}(x)\cdot y)$ is maximized and $(\sum_{x\in\mathcal{X}_{\hat{h},S}^-} \hat{p}(x)\cdot y)$ is minimized. This implies $\hat{h}$ maximizes the function $\mu(h, S)$.

F MISSING PROOFS FROM SECTION 5

Lemma 5.2. *Let $k \le k_2$. Then for every $h \in H_k$, the induced complexity of the corresponding f_h is $\ell \le k$.*

Proof. Let $\ell = \min_{k' \in [1,k]}\{\text{there exists a } g : \mathcal{Z}_\ell \to \{\pm 1\} \text{ such that } h = \text{lift}(g)\}$. From Lemma A.4, we know $\ell \le k$. Further, assume $g : \mathcal{Z}_\ell \to \{\pm 1\}$ is such that $h = \text{lift}(g)$. Now, from the definition of f_h, we have for all $x \in \mathcal{X}$, $f_h(x) = 1$ if and only if there exists a $z \in \mathcal{Z}$ such that $z \subset x$ and $h(z) = 1$. Since $h \in H_k$, for all $x \in \mathcal{X}$ $f_h(x) = 1$ if and only if there exists a $z \in \mathcal{Z}$, $|z| \ge k \ge \ell$ such that $z \subset x$ and $h(z) = 1$. Finally, as $h = \text{lift}(g)$, $f_h(x) = 1$ if and only if there exists a $z \in \mathcal{Z}_\ell$ such that $z \subset x$ and $g(z) = 1$. □

Corollary 5.3. *Let $F_k = F_{H_k}$ be the induced function class of H_k, as defined in Def. 4.5. Then:*

$$F_k = \{f : \mathcal{X} \to \{\pm 1\} \ : \ f \text{ has induced complexity } \ \le k\}$$

Proof. From Lemma 5.2, we know that functions in F_k have induced complexity at most k. We show that if f has induced complexity at most k then there is an $h \in H_k$ such that $f = f_h$. Let the induced complexity of f be equal to $\ell \le k$. Then there exists a $g : \mathcal{Z}_\ell \to \{\pm 1\}$ such that

$$\begin{aligned} f(x) = 1 \text{ if and only if there exists a } z \in \mathcal{Z}_\ell \\ \text{such that } z \subseteq x \text{ and } g(z) = 1. \end{aligned} \tag{12}$$

Define $h : \mathcal{Z} \to \{\pm 1\}$ as follows

$$h(z) = \begin{cases} 1 & \text{if } \ \exists z' \subseteq z, |z'| = \ell \text{ and } g(z) = 1 \\ -1 & \text{o.w.} \end{cases}$$

First, we show that $f(x) = f_h(x)$ for all $x \in \mathcal{X}$. From the above definition of h, it follows that

$$\begin{aligned} g(z) = 1 \text{ for } z \in \mathcal{Z}_\ell \\ \Rightarrow \text{ for all } z \in \mathcal{Z} \text{ such that } z' \subseteq z, h(z) = 1. \end{aligned} \tag{13}$$

Hence, from Equation 12 and 13 for all $x \in \mathcal{X}$, $f(x) = 1$ if and only if there exists $z \in \mathcal{Z}$ such that $h(z) = 1$. This implies $f(x) = f_h(x)$ for all $x \in \mathcal{X}$.

To show $h \in H_k$, we construct a weight function w on size k sets. For $z \in \mathcal{Z}_k$, let

$$w(z) \begin{cases} > \sum_{i \in [1,k]} \binom{n}{i} & \text{if } \ \exists z' \subseteq z, |z'| = \ell \text{ and } g(z) = 1 \\ \in (-1, 0) & \text{o.w.} \end{cases}$$

Now it is easily verified that for all $z \in \mathcal{Z}$

$$h(z) = \text{sign}\left(\sum\nolimits_{z' : z' \subseteq z, |z'| \le k} w(z')\right)$$

implying $h \in H_k$. □

Corollary 5.5. *If $\ell^* \le k_2$ and the distribution D has full support on $\mathcal{X}$, then $k = \ell^*$ is the smallest k that gives zero approximation error.*

Proof. In the proof of Theorem 5.4, we show that for $k = \ell^*$, we have zero approximation error. Hence, to prove the corollary it is sufficient to show that for a $k < \ell^*$ the approximation error is not zero. Suppose there is an $h \in H_k$ such that $\varepsilon(h) = 0$ and $k < \ell^*$. Since the distribution D has full support, this implies $f_h(x) = v(x)$ for all $x \in \mathcal{X}$. Hence, the induced complexity of v is $k < \ell^*$ giving a contradiction. □

Corollary 5.6. *If $\ell^* > k2$, then the approximation error weakly increases with k, i.e., $H_k \le H_{k-1}$ for all $k \le k_2$. Furthermore, if the distribution D has full support on $\mathcal{X}$ then no k can achieve zero approximation error.*

Proof. The approximation error weakly decreases because $H_{k-l} \subset H_k$ for all $k \le k_2$. Also, from the proof of Corollary 5.5 it is clear that no k can achieve zero approximation error. □

Lemma 5.10. *There exists a distribution D and a value function v such that for all $k < k' \le k_2$, system has higher payoff against the optimal $h_k^* \in H_k$ than against $h_{k'}^* \in H_{k'}$.*

Proof. The v constructed is as in the proof Theorem 5.7. We recall notations from the proof of Theorem 5.7: z_e is a k_2 size subset. Further, in the proof of Theorem 5.7 we argue that for $k \in [1, k_2]$, h_k^* is such that for all $z \in \mathcal{Z}$, $h^*(z) = 1$ if and only if there exists a k size $z' \subset z$ which is also a subset of z_e.

Now let $k, k' \in [1, k_2]$ such that $k < k'$. Since D is the uniform distribution, to show system's utility is more for k compared to k' it is sufficient to show that

$$\sum_{x \in \mathcal{X}} \mathbb{1}\{h_k^*(\phi_{h_k^*}(x)) = 1\} > \sum_{x \in \mathcal{X}} \mathbb{1}\{h_{k'}^*(\phi_{h_{k'}^*}(x)) = 1\}$$

From the proof of Theorem 5.7 and Theorem 4.6, it follows that

$$\sum_{x\in\mathcal{X}} \mathbb{1}\{h_k^*(\phi_{h_k^*}(x)) = 1\} = \sum_{x\in\mathcal{X}} \mathbb{1}\{f_{h_k^*}(x) = 1\} = \sum_{\ell=k}^{k_2} \binom{k_2}{\ell}\binom{q-k_2}{n-\ell}$$

Similarly,

$$\sum_{x\in\mathcal{X}} \mathbb{1}\{h_{k'}^*(\phi_{h_{k'}^*}(x)) = 1\} = \sum_{\ell=k'}^{k_2} \binom{k_2}{\ell}\binom{q-k_2}{n-\ell}$$

Since $k < k'$, it is easy to see that

$$\sum_{x\in\mathcal{X}} \mathbb{1}\{f_{h_k^*}(x) = 1\} = \sum_{\ell=k}^{k_2} \binom{k_2}{\ell}\binom{q-k_2}{n-\ell} > \sum_{\ell=k'}^{k_2} \binom{k_2}{\ell}\binom{q-k_2}{n-\ell}$$

implying system's utility is more for k compared to k'. □

Corollary 5.11. *For the system, lower k_2 is better (in a worst-case sense).*

Proof. In Theorem 5.10, we showed there exists a user with v such that for all $k, k' \in [1, k_2]$ and $k < k'$, the system has better utility against the optimal choice function in H_k than in $H_{k'}$. Since the choice of k the user can make is bounded by k_2, a lower k_2 maximizes the worst-case payoff to the system. □