An α-regret analysis of Adversarial Bilateral Trade

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Abstract

We study sequential bilateral trade where sellers and buyers valuations are completely arbitrary (*i.e.*, determined by an adversary). Sellers and buyers are strategic agents with private valuations for the good and the goal is to design a mechanism that maximizes efficiency (or gain from trade) while being incentive compatible, individually rational and budget balanced. In this paper we consider gain from trade which is harder to approximate than social welfare.

We consider a variety of feedback scenarios and distinguish the cases where the mechanism posts one price and when it can post different prices for buyer and seller. We show several surprising results about the separation between the different scenarios. In particular we show that (a) it is impossible to achieve sublinear α-regret for any $\alpha < 2$, (b) but with full feedback sublinear 2-regret is achievable (c) with a single price and partial feedback one cannot get sublinear α regret for any constant α (d) nevertheless, posting two prices even with one bit feedback achieves sublinear 2-regret, and (e) there is a provable separation in the 2-regret bounds between full and partial feedback.

1 Introduction

The bilateral trade problem arises when two rational agents, a seller and a buyer, wish to trade a good; they both hold a private valuation for it, and their goal is to maximize their utility. The solution of the problem consists in designing a mechanism that intermediates between the two parties to make the trade happen. Ideally, the mechanism should maximize social welfare even though the agents act strategically (*incentive compatibility*) and should guarantee non-negative utility to the agents (*individual rationality*). Furthermore, we are interested in mechanisms for bilateral trade that do not subsidize the agents (*budget balanced*). Obvious mechanisms that satisfy incentive compatibility, individual rationality, and budget balanced, are posted price mechanisms. Two common metrics are used to measure the efficiency of a mechanism: social welfare subsequent to trade and gain from trade (*i.e.*, the increase in social welfare). Consider a mechanism that posts prices p (price for the seller) and q (price for the buyer) to agents with valuations s and b, formally we have:

- **Social Welfare**: $\mathrm{SW}(p, q, s, b) = s + (b - s) \cdot \mathbb{I}\{s \leq p \leq q \leq b\}$[1]
- **Gain from trade**: $\mathrm{GFT}(p, q, s, b) = (b - s) \cdot \mathbb{I}\{s \leq p \leq q \leq b\}$

It is clear from these expressions that if we are interested in exact optimality then maximizing gain from trade is equivalent to maximizing social welfare. However, Myerson and Satterthwaite [1983] showed that there are *no mechanisms* for bilateral trade that are simultaneously social welfare maximizing (alternately, gain from trade maximizing), incentive compatible, individually rational,

[1] We use $\mathbb{I}\{Q\}$ for the indicator variable that takes the value 1 if the predicated Q is true and zero otherwise.

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and budget balanced[2]. It follows that the best one can hope for is an incentive compatible, individually rational, and budget balanced mechanism that approximates the optimal social welfare. This creates an asymmetry between the two metrics: a multiplicative c approximation to the maximal gain from trade implies an approximation at least as good ($\geq c$) to the maximal social welfare but not vice versa. Ergo, it is harder to approximate the gain from trade than to approximate social welfare. For example, consider an instance where the seller has valuation 0.99 and the buyer is willing to pay up to 1: irrespective of if a trade occurs or not, 99% of the optimal social welfare is guaranteed. *I.e.*, a mechanism that posts a price of zero and generates no trade gets a good approximation to the social welfare. Contrariwise, the gain from trade is non-zero only if the mechanism manages to post prices in the narrow $[0.99, 1]$ interval.

The vast body of work subsequent to Myerson and Satterthwaite [1983] primarily considers the Bayesian version of the problem, where agents' valuations are drawn from some distribution and the efficiency is evaluated in expectation with respect to the valuations' randomness. There are many incentive compatible mechanisms that give a constant approximation to the social welfare (in the Bayesian setting), e.g., see Blumrosen and Dobzinski [2014]. On the other hand, finding a constant approximation to the gain from trade has been a long standing problem and only a very recent paper of Deng et al. [2021] has given a Bayesian incentive compatible mechanism for this problem. In this paper we deal with the harder scenario where an adversary determines seller and buyer valuations (*i.e.*, valuations are not drawn from some distribution). Ergo, positive results in the Bayesian setting are inapplicable in our setting.

Following Cesa-Bianchi et al. [2021a], we consider the sequential adversarial bilateral trade problem, where at each time step t, a new seller-buyer pair arrives. The seller has some private valuation $s_t \in [0, 1]$ representing the smallest price she is willing to accept; conversely, the buyers holds as private information $b_t \in [0, 1]$, *i.e.*, the largest price she is willing to pay to get the good. Note that by individual rationality and budget balance, a trade can only happen if $s_t \leq b_t$. Concurrently, the mechanism posts price p_t to the seller and q_t to the buyer. If they both accept, then the trade happens at those prices, otherwise the agents leave forever. By the requirement that the mechanism be budget balanced, the prices posted by the mechanism are such that $p_t \leq q_t$. At the end of each time step, the mechanism receives some feedback that depends on the outcome of the trade. Ideally, we would like to have a strategy for the sequential bilateral trade problem whose average gain from trade converges to that of the best fixed posted price mechanism in insight. However, as Cesa-Bianchi et al. [2021a] recently showed, this is a hopeless task.

Our goal in this work is then to achieve mechanisms whose average performance converges to a constant factor of the best fixed posted price mechanism in hindsight. We would like to find the smallest $\alpha \geq 1$ such that the α-regret [Kalai and Vempala, 2005] is sublinear in the time horizon T:

$$\max_{p,q} \sum_{t=1}^{T} \mathrm{GFT}(p, q, s_t, b_t) - \alpha \cdot \mathbb{E}\left[\sum_{t=1}^{T} \mathrm{GFT}(p_t, q_t, s_t, b_t)\right].$$

If the goal is only to maximize gain from trade, there is never any sense in offering two different prices (to the seller and buyer). However, critically, offering two prices is provably helpful in the context of a learning algorithm.

To conclude the description of our learning framework, we specify the type of feedback received by the mechanism. We focus on the two extremes of the feedback spectrum. On the one hand we study the full feedback model, where, after prices are posted, the mechanism learns both seller and buyer valuations (s_t, b_t). We study also study more realistic *partial feedback* models such as *one bit feedback*, where the learner only discovers if a trade took place or not. We also study an intermediate model, called the *two bit feedback model*. In this model, the learner posts (one or two) prices, and learns if the buyer is willing to trade and if the seller is willing to trade, at these prices. Clearly, a trade actually occurs only if both are willing to trade. Note that these two models enforce the desirable property that buyers and sellers only communicate to the mechanism a minimal amount of information useful for the trade, without disclosing their actual valuations.

[2]This impossibility result holds even when the (private) agents valuations are assumed to be drawn from some (public) random distributions and the incentive compatibility is only enforced in expectation.

	Full Feedback	Two bit feedback	One bit feedback
Single price	$O(\sqrt{T})$ - Theorem 2	$\Omega(T)$ - Theorem 4	
Two prices	$\Omega(\sqrt{T})$ - Theorem 3	$\Omega(T^{2/3})$ - Theorem 6	$O(T^{3/4})$ - Theorem 5

Table 1: Summary of 2-regret results in various settings.

1.1 Overview of our Results

We present now our results for the adversarial sequential bilateral trade problem (see also Table 1).

- We show that no learning algorithm can achieve sublinear α-regret for any $\alpha < 2$ (Theorem 1). This holds in the full feedback model (and thus for both partial feedback models).
- We give a learning algorithm with full feedback that achieves $\tilde{O}(\sqrt{T})$ 2-regret[3] (Theorem 2) and show that no algorithm can improve upon this (Theorem 3).
- We show that if limited to a single price, no learning algorithm achieves sublinear α-regret for any constant α in either partial feedback models, *i.e.*. given either one or two bit feedback (Theorem 4).
- Given the negative results above, we show that allowing two prices gives sublinear 2-regret even for one bit feedback (Theorem 5). This means that our algorithm is able to achieve at least half of the gain from trade, on average, of the best fixed price in hindsight, using only one bit of feedback at each step.
- We show a separation between one bit (or two bit) feedback versus full feedback by giving a $\Omega(T^{2/3})$ lower bound on the 2-regret for any learning algorithm (Theorem 6).

One may wonder why two prices are helpful at all, given their suboptimality in maximizing the gain from trade. As already mentioned before, choosing a single price between the posted price to the seller and the posted price of the buyer is always at least as successful in terms of the success of the bilateral trade. This is a bit surprising as the sequence is worst case and there is no correlation between the history and future valuations of pairs of buyer and seller. In particular, what we learned at step t may be, in principle, completely irrelevant for future requests. It is also worth noting that in our worst case model two prices are required but one bit suffices for 2-regret. This is a different qualitative behaviour that the one observed in the stochastic case [Cesa-Bianchi et al., 2021a], where it is enough to use one single price but two bit feedback is required to achieve sublinear (1-)regret.

1.2 Technical challenges

From experts to prices. As already observed in Cesa-Bianchi et al. [2021a], the full feedback model nicely fits into the prediction with experts framework [Cesa-Bianchi and Lugosi, 2006]: there is a clear mapping between expert and prices and the mechanism can easily reconstruct the gain that each price/expert experiences using the feedback received. The main challenge here is given by the continuous nature of the possible prices, as the usual experts framework assumes a finite number of experts. There are workarounds that exploit some regularity of the gain function such as the Lipschitz property or convexity/concavity [see, e.g., Cesa-Bianchi and Lugosi, 2006, Hazan, 2016, Slivkins, 2019]. Unfortunately, gain from trade is not such a function. Moreover, in our adversarial setting we cannot adopt the smoothing trick used in Cesa-Bianchi et al. [2021a], where they assume some regularity on the agents distribution to argue that $\mathbb{E}\left[\mathrm{GFT}(\cdot)\right]$ becomes Lipschitz. Our main technical tool to address this issue is a discretization claim that allows us to compare the performance of the best fixed price in $[0, 1]$ with that of the best on a finite grid.

A magic estimator. Consider any of the two partial feedback models; there at each time step t the learner only receives a minimal information about what happened at time t: namely, one or two bit versus the full knowledge of $\mathrm{GFT}_t(\cdot)$. Note that this type of feedback is strictly more difficult than the classic bandit feedback [Cesa-Bianchi and Lugosi, 2006], where the learner always observes at least the gain its action incurred. Our main technical tool to circumvent this issue is given by the design of a procedure that, posting two randomized prices, is able to estimate the GFT_t in a given price. This unbiased estimator is then used in a carefully designed block decomposition of the time horizon to achieve sublinear 2-regret in presence of this very poor feedback.

[3] The $\tilde{O}$ hides poly-logarithmic terms

Lower bounds. For our lower bounds we adopt two different strategies. In Theorem 1 and 4 we construct randomized instances where no algorithm can learn anything: the only prices the learner could use to discriminate between different instances are carefully hidden, while all the other prices do not reveal any useful information, given the type of feedback considered. The randomized instances used in Theorem 3 and 6 involve instead a more structured approach; this is due to the challenge posed by the contemporary handling of the multiplicative and additive part of the 2-regret. To this end, we carefully hide the optimal ex-post prices and make hard to the learner to achieve small (1-)regret with respect to some "second best" prices. A crucial task we often face is to "hide" some small finite sets of critical prices from the learning algorithm. We employ two techniques to do so: (a) random shifts (as in the proof of Theorem 4) and (b) repeatedly dividing overlaps (Theorem 1 and 3).

1.3 Related work

The work that is most closely related to ours is Cesa-Bianchi et al. [2021a]. There, the authors study the same sequential bilateral trade problem as we do, with the objective of minimizing the (1-)regret with respect to the best fixed price. They focus on the (easier) stochastic model, where the adversary chooses a distribution over valuations and not a deterministic sequence like in our model. A full characterization of the minimax regret regimes is offered, for the same type of feedback we consider (not that the one bit feedback is only addressed in their extended version [Cesa-Bianchi et al., 2021b]) and with various regularity assumptions on the underlying random distributions. Cesa-Bianchi et al. [2021a] also give the first result for the adversarial setting we consider, showing that no learning algorithm can achieve sublinear 1-regret.

Regret minimization in the context of economics has been studied in many papers [e.g., Morgenstern and Roughgarden, 2015, Cesa-Bianchi et al., 2015, Daskalakis and Syrgkanis, 2016, Lykouris et al., 2016]. In particular, Kleinberg and Leighton [2003] studied the one-sided pricing problem, offering a $\tilde{O}(T^{2/3})$ upper bound on the regret in the adversarial setting and opening a fruitful line of research [Blum et al., 2004, Blum and Hartline, 2005, Bubeck et al., 2019]. The notion of α-regret has been formally introduced by Kakade et al. [2009], but was already present in Kalai and Vempala [2005]. It has then found applications in linear [Garber, 2021] and submodular optimization [Roughgarden and Wang, 2018], learning with sleeping actions [Emamjomeh-Zadeh et al., 2021], combinatorial auctions [Roughgarden and Wang, 2019] and market design [Niazadeh et al., 2021]. While Myerson and Satterthwaite [1983] were the first to thoroughly investigate the bilateral trade problem in the Bayesian setting with their famous impossibility result, it was the seminal paper of Vickrey [Vickrey, 1961] that introduced the problem, proving that any mechanism this is welfare maximizing, individually rational, and incentive compatible is not budget balanced.

In the Bayesian setting, it was only very recently that Deng et al. [2021] gave the first (Bayesian) incentive compatible, individually rational and budget balance mechanism achieving a constant factor approximation of the optimal gain from trade. Prior to this paper, a posted price $O\big(\log \frac{1}{r}\big)$ approximation bound was achieved by [Colini-Baldeschi et al., 2017], with r being the probability that a trade happens (i.e., the value of the buyer is higher than the value of the seller). The literature also includes many individually rational, incentive compatible and budget balanced mechanisms achieving a constant factor approximation of the optimal social welfare. Blumrosen and Dobzinski [2014] proposed a simple posted price mechanism, the median mechanism, yielding a 2-approximation of the optimal social welfare; the same authors then implemented a randomized fixed price mechanism improving the approximation to $e/(e-1)$ [Blumrosen and Dobzinski, 2021]. Recently, Dütting et al. [2021] showed that even posting one single sample from the seller distribution as price is enough to achieve a 2 approximation to the optimal social welfare. The class of fixed price mechanism is of particular interest as it has been showed that all (dominant strategy) incentive compatible and individually rational mechanisms that enforce a stricter notion of budget balance, i.e., the so-called strong budget balance (where the mechanism is not allowed to subsidize or extract revenue from the agents) are indeed fixed price [Hagerty and Rogerson, 1987, Colini-Baldeschi et al., 2016].

2 Preliminaries

The formal protocol for the sequential bilateral trade follows Cesa-Bianchi et al. [2021a]. At each time step t, a new pair of seller and buyer arrives, each with private valuations s_t and b_t in $[0,1]$; the learner posts two prices: $p_t \in [0,1]$ to the seller and $q_t \in [0,1]$ to the buyer. A trade happens if and

Learning Protocol of Sequential Bilateral Trade

for time $t = 1, 2, \ldots$ **do**
a new seller/buyer pair arrives with (hidden) valuations $(s_t, b_t) \in [0,1]^2$
the learner posts prices $p_t, q_t \in [0,1]$
the learner receives a (hidden) reward $\mathrm{GFT}_t(p_t, q_t) := \mathrm{GFT}(p_t, q_t, s_t, b_t) \in [0,1]$
a feedback z_t is revealed

only if both agents agree to trade, i.e., when $s_t \le p_t \le q_t \le b_t$. Since we want our mechanism to enforce weakly budget balance, we require that $p_t \le q_t$ for all t. When a trade occurs, the learner is awarded with the resulting increase in social welfare, i.e., $b_t - s_t$. The learner then observes some feedback z_t. The gain from trade at time t depends on the valuations s_t and b_t and on the price posted. To simplify the notation we introduce the following:

$$\mathrm{GFT}_t(p,q) := \mathrm{GFT}(p,q,s_t,b_t) = \mathbb{I}\{s_t \le p \le q \le b_t\} \cdot (b_t - s_t)$$

When the two prices are equal, we omit one of the arguments to simplify the notation.

Given any constant $\alpha \ge 1$, we define the α-Regret of a learning algorithm $\mathcal{A}$ against a sequence of valuations $\mathcal{S}$ on time horizon T as follows

$$R_T^{\alpha}(\mathcal{A}, \mathcal{S}) := \max_{p,q \in [0,1]^2} \sum_{t=1}^{T} \mathrm{GFT}_t(p,q) - \alpha \cdot \sum_{t=1}^{T} \mathbb{E}\left[\mathrm{GFT}_t(p_t, q_t)\right].$$

In the right side of the equation the dependence on $\mathcal{S}$ is contained in the $\mathrm{GFT}_t(\cdot)$. Note that the expectation in the previous formula is with respect to the internal randomization of the learning algorithm: p_t and q_t are the (possibly random) prices posted by $\mathcal{A}$.

The α-regret of a learning algorithm $\mathcal{A}$, without specifying the dependence of the sequence, is defined as its α-regret against the "worst" sequence of valuations: $R_T^{\alpha}(\mathcal{A}) := \sup_{\mathcal{S}} R_T^{\alpha}(\mathcal{A}, \mathcal{S})$. Stated differently, the performance of an algorithm is measured against an oblivious adversary that generates the sequence of valuations ahead of time: the learner has to perform well on *all* possible sequences. In this paper we study the minimax α-regret. The minimax regret is denoted $R_T^{\alpha,\star}$ and measures the performance of the best (learning) algorithm versus the optimal solution, on the worst possible instance: $R_T^{\alpha,\star} := \inf_{\mathcal{A}} R_T^{\alpha}(\mathcal{A})$. The set of learning algorithms we consider depends on which of the various settings we are dealing with. In this paper we consider a variety of such settings (*i.e.*, how many prices are posted, what feedback is available, see below Sections 2.1 and 2.2).

2.1 Single Price *vs.* Two Prices — Seller price and Buyer price

We consider two families of learning algorithms, differing in the nature of the probe they perform, corresponding to two notions of what it means to be budget balanced:

Single price mechanisms. If we want to enforce a stricter notion of budget balance, namely strong budget balance, the mechanism is neither allowed to subsidize nor extract revenue from the system. This is modeled by imposing $p_t = q_t$, for all t. If $p_t = q_t$ we use the notation $\mathrm{GFT}_t(p_t)$ to represent the gain from trade at time t.

Two price mechanisms. If we require that the mechanism enforces (weak) budget balance, it can post two different prices, p_t to the seller and q_t to the buyer, as long as $p_t \le q_t$. *I.e.*, we only require that the mechanism never subsidize a trade, we do not require that the mechanism not make a profit. In this setting we use the notation $\mathrm{GFT}_t(p_t, q_t)$ to represent the gain from trade at time t.

Observation 1. *Note that the only reason to post two prices is to obtain information. For any pair of prices (p,q) with $p < q$ posting any single price $\pi \in [p,q]$ guarantees no less gain from trade.*

In particular, any budget balanced algorithm that knows the future and seeks to maximize gain from trade while repeatedly posting the same prices will never choose two different prices.

2.2 Feedback models

We consider three types of feedback, presented here in increasing order of difficulty for the learner. (Note that full feedback "implies" two bit feedback which in turn implies one bit feedback):

Full feedback. In the full feedback model, the learner receives both seller and buyer valuations, immediately after posting prices the feedback to the learner at time t is $z_t = (s_t, b_t)$. E.g., both seller and buyer send sealed bids that are opened immediately after the [one or two] price[s] are revealed. It follows from Observation 1 that in the full feedback model there is never any reason to post two prices, all the relevant information is revealed anyway.

Two bit feedback. In two bit feedback the algorithm observes separately if the two agents agree on the given price, *i.e.*, the feedback at time t, $z_t = (\mathbb{I}\{p_t \geq s_t\}, \mathbb{I}\{q_t \leq b_t\})$.

One bit feedback The one bit feedback is arguably the minimal feedback the learner could get. Here the the only information revealed is whether the trade occurred or not, *i.e.*, the feedback at time t is $z_t = \mathbb{I}\{s_t \leq p_t \leq q_t \leq b_t\}$.

2.3 Regret due to discretization

Our first theoretical result concerns the study of how discretization impacts the regret. In particular, we compare the performance of the best fixed price taken from the continuous set $[0, 1]$ to that of the best fixed price chosen from some discrete grid $Q \subset [0, 1]$. Optimizing over a continuous set or over a discrete subset may seemingly be a problem because our object, gain from trade, is discontinuous (thus non-Lipschitz), non-convex and non-concave; one cannot use the "standard approach" that makes use of such regularity conditions. What we show in the following Claim (whose proof is deferred to the appendix together with all the other missing proofs) is that it is possible to compare the performance of the best continuous fixed price with *twice* that of the best fixed price on the grid.

Claim 1 (Discretization error)**.** *Let $Q = \{q_0 = 0 \leq q_1 \leq q_2 \cdots \leq q_n = 1\}$ be any finite grid of prices in $[0, 1]$ and let $\delta(Q)$ be the largest difference between two contiguous prices, i.e., $\max_{i=1,\ldots,n} |q_i - q_{i-1}|$, then for any sequence $\mathcal{S} = (s_1, b_1), \ldots, (s_T, b_T)$ and any price p we have*

$$\sum_{t=1}^{T} \mathrm{GFT}_t(p) \leq 2 \cdot \max_{q \in Q} \sum_{t=1}^{T} \mathrm{GFT}_t(q) + \delta(Q) \cdot T.$$

Let $\mathcal{A}$ be any learning algorithm that posts prices (p_t, q_t), then the following inequality holds:

$$R_T^2(\mathcal{A}) \leq 2 \sup_{\mathcal{S}} \left\{ \max_{q \in Q} \sum_{t=1}^{T} \mathrm{GFT}_t(q) - \sum_{t=1}^{T} \mathbb{E}\left[\mathrm{GFT}_t(p_t)\right] \right\} + \delta(Q) \cdot T. \tag{1}$$

Before moving to the next section, we spend some words to compare our discretization result with the one in Cesa-Bianchi et al. [2021a] (Second decomposition Lemma). As already mentioned, there the authors exploit the stochastic nature of the valuations to argue that $\mathbb{E}\left[\mathrm{GFT}_t(\cdot)\right]$ is Lipschitz, under some regularity assumptions on the random distributions. We study the adversarial model, thus we cannot use this "smoothing" procedure; this is why we lose an extra multiplicative factor of 2.

3 Full Feedback

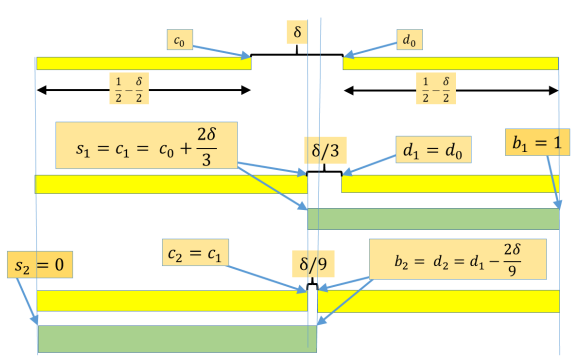

Figure 1: Lower bound construction that "hides" the optimal price.

In this section we study the gain from trade learning problem in the full feedback model, where the learner receives feedback $z_t = (s_t, b_t)$ after posting a [single] price (follows from Observation 1). Given that the mechanism knows both seller and buyer valuations it can evaluate $\mathrm{GFT}_t(p)$ for all $p \in [0, 1]$ after posting any price. As already mentioned, there is a clear connection with the prediction with experts framework [Cesa-Bianchi and Lugosi, 2006] and the main difference between the two is given by the specific structure of the our objective (whereas in the expert case arbitrary

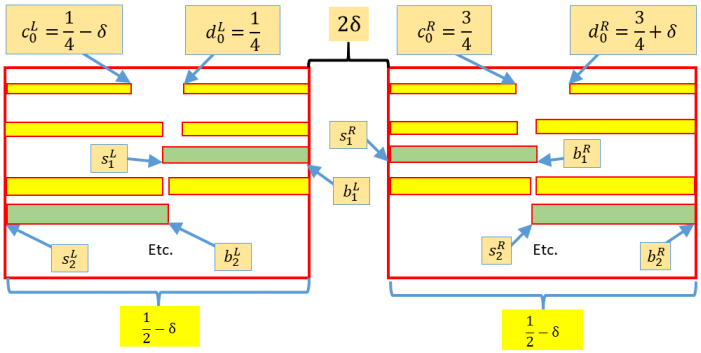

Figure 2: The proof of Theorem 3 makes use of two (appropriately scaled and shifted) copies of the lower bound from Theorem 1 (See Figure 1). In this example the left hand copy choose right and then left, while the right hand copy happened to choose left and then right. The (seller,buyer) bids at time t are then chosen independently at random from (s_t^L, b_t^L) and (s_t^R, b_t^R).

gain vectors are allowed) and the cardinality of the action space: we need to be competitive against a continuum of prices in the real range $[0, 1]$. We start by showing that the impossibility result from Cesa-Bianchi et al. [2021a], *i.e.*, no learning algorithm achieves sublinear regret (1-regret) in the sequential bilateral trade problem, can be extended to hold for α-regret for all $\alpha \in [1, 2)$.

Theorem 1 (Lower bound for $(2-\varepsilon)$-regret)**.** *In the full-feedback model, for all $\varepsilon \in (0, 1]$ and horizons T, the minimax $(2-\varepsilon)$-regret satisfies $R_T^{2-\varepsilon,\star} \geq \frac{1}{8}\varepsilon T$.*

The idea behind the proof of Theorem 1 is to construct a randomized family of instances such that any deterministic learner would suffer linear $2-\varepsilon$ regret. Specifically, any sequence from the randomized family consists of (sell,buy) prices that have the form $(0, b_i)$ or $(s_i, 1)$. The sequence is generated iteratively in a way such that all realized segments overlap and the next segment is chosen at random among two disjoint options $(0, b_i)$ or $(s_i, 1)$. Since all realized segments overlap, there is one price in the intersection of all intervals and this is the optimal fixed price in hindsight; conversely, at each time step no learner can post a price that guarantees a trade with probability greater than $1/2$. This gives the lower bound. A pictorial representation of this process appears in Figure 1, where the green intervals refer to a realization of the first two (sell,buy) pairs and the yellow intervals represent an auxiliary structure used to guarantee all the desired properties; more in the appendix.

As already mentioned, our model shares strong similarities with the prediction with experts framework. In particular, if we simplify the task of the learner and ask it to be competitive against a finite grid of prices, we can use results on experts as a black box. Combining this fact with our discretization result, we can show an $\tilde{O}(\sqrt{T})$ upper bound on the 2-regret for the bilateral trade problem.

Theorem 2 (Upper bound on 2-regret given full feedback)**.** *In the full-feedback setting, there exists a learning algorithm $\mathcal{A}$ whose 2-regret, for T large enough, respects $R_T^2(\mathcal{A}) \leq 5 \cdot \sqrt{T \cdot \log T}$.*

We conclude this section by presenting a theorem showing that the bound on the 2-regret obtained in the previous theorem is tight up to a logarithmic factor, i.e., the minimax 2-regret of the full feedback problem is $\tilde{\Theta}(\sqrt{T})$. The proof uses two copies of the construction described in Figure 1 together with a classical lemma about random walks (see **??**) given in the appendix. A pictorial description of the lower bound construction appears in Figure 2.

Theorem 3 (Lower bound on 2-regret given full feedback)**.** *In the full-feedback model, for all horizons T large enough, the minimax 2-regret satisfies $R_T^{2,\star} \geq \frac{1}{13}\sqrt{T}$.*

4 Partial Feedback

In this section, we study the partial feedback models. Here, the learner receives very limited information on the realizations of the gain from trade. Specifically, one or two bit feedback that describes the relative positions of the prices proposed to the agents and their valuations.

Estimation procedure of GFT using two prices and one bit feedback

Input: price p
Toss a biased coin with head probability p
if head **then** Draw U u.a.r. in $[0, p]$ and set $\hat{p} \leftarrow U$, $\hat{q} \leftarrow p$
else Draw V u.a.r. in $[p, 1]$ and set $\hat{p} \leftarrow p$, $\hat{q} \leftarrow V$
Post price $\hat{p}$ to the seller and $\hat{q}$ to the buyer and observe the one bit feedback $\mathbb{I}\{s \leq \hat{p} \leq \hat{q} \leq b\}$
Return: $\widehat{\mathrm{GFT}}(p) \leftarrow \mathbb{I}\{s \leq \hat{p} \leq \hat{q} \leq b\}$

4.1 Lower bound on α-regret posting single price given two bit feedback

Consider a learner that is constrained to post one single price at every iteration; the same to both seller and buyer. For this class of algorithms we show a very strong impossibility result, namely that for any constant α, there exists no algorithm achieving sublinear α-regret. We prove this in the two bit feedback model and thus it trivially holds also if given one bit feedback. The main idea underlying the lower bound construction is that it is possible to hide a *large* interval between many shorter ones; a learner posting only one price will not be able to locate it given the type of feedback it receives (which consists in just *counting* the number of intervals on the left and on the right).

Theorem 4 (Lower bound on α-regret posting single price, two bit feedback)**.** *In the two bit feedback model where the learner is allowed to post one single price, for all horizons $T \in \mathbb{N}$ and any constant $\alpha > 1$, the minimax α-regret satisfies $R_T^{\alpha,\star} \geq \frac{1}{128\alpha^3} T$.*

4.2 Upper bound on the 2-regret, posting two prices and given one bit feedback

The main result in this section is Theorem 5 which shows that one can achieve sublinear 2-regret with one bit feedback (and by posting two prices). We find this to be the most surprising result in this paper. The crucial ingredient for our construction of a sublinear 2-regret algorithm is an unbiased estimator, ($\widehat{\mathrm{GFT}}$) of the gain from trade that uses two prices and *one single bit* of feedback. This seems quite remarkable. The gain from trade is a discontinuous function composed by two different objects: the difference $(b - s)$ and the indicator variable $\mathbb{I}\{p \in [s, b]\}$. Both these two objects are easy to estimate *independently*, but for the gain from trade we need an estimator of their product. We construct an estimation procedure that considers both features at the same time: it tosses a biased coin with head probability p; if head, it posts price p to the buyer and a price drawn u.a.r. in $[0, p]$ to the seller; if tails, it posts price p to the seller and a price drawn u.a.r. in $[p, 1]$ to the buyer. The formal procedure is described in the pseudocode. The following lemma proves that this procedure yields an unbiased estimator of the gain from trade.

Lemma 1. *Fix any agents' valuations $s, b \in [0, 1]$. For any price $p \in [0, 1]$, it holds that $\widehat{\mathrm{GFT}}(p)$ is an unbiased estimator of $\mathrm{GFT}(p)$: $\mathbb{E}\left[\widehat{\mathrm{GFT}}(p)\right] = \mathrm{GFT}(p)$, where the expectation is with respect to the randomness of the estimation procedure.*

The estimation procedure is then a powerful tool that allows the learner to estimate the gain from trade it would have extracted at time t posting price p using randomization and *one single bit* of feedback. Note here that the possibility of posting two different prices is crucial: as we have argued in the previous section, one single price is not able to do that, even for two bit feedback. Given the estimator $\widehat{\mathrm{GFT}}$ we present our learning algorithm BLOCK-DECOMPOSITION. Similarly to what is done in Chapter 4 of Nisan et al. [2007], the learner divides the time horizon in S time blocks B_τ of equal length and uses as subroutine some expert algorithm $\mathcal{E}$ on a meta-instance that considers each time block as a time step and each price in a suitable grid Q as an action. In each block the learner posts the same price p_τ in all but $|Q|$ time steps, where it uses $\widehat{\mathrm{GFT}}$ to estimate the total gain from trade obtained in B_τ by all prices in Q. The details of BLOCK-DECOMPOSITION are presented in the pseudocode. Before delving into the bound on the 2-regret, we formalize our second estimation claim in the following Lemma.

Lemma 2. *Fix a grid Q of prices in $[0, 1]$ and any sequence of Δ (seller,buyer) valuations. Let $h : Q \to [\Delta]$ be a map drawn uniform at random between all the injective functions from Q and $[\Delta]$. Then the following equality holds for all prices $p_i \in Q$: $\mathbb{E}\left[\widehat{\mathrm{GFT}}_{h^{-1}(p_i)}(p_i)\right] = \frac{1}{\Delta}\sum_{t=1}^{\Delta} \mathrm{GFT}_t(p_i)$, the expectation is with respect to the random choice of h and the internal randomness of the estimator.*

BLOCK-DECOMPOSITION (BD)

Input: time horizon T, number of blocks S, grid Q and expert algorithm $\mathcal{E}$
$\Delta \leftarrow T/S$, $K \leftarrow |Q|$
$B_\tau \leftarrow \{(\tau-1)\cdot\Delta+1,\dots,\tau\cdot\Delta\}$, for all $\tau = 1,\dots S$
Initialize $\mathcal{E}$ with time horizon S and K actions, one for each $p_i \in Q$
for each round $\tau = 1, 2, \dots, S$ **do**
    Receive from $\mathcal{E}$ the price p_τ
    Select uniformly at random an injection $h_\tau : Q \to B_\tau$ ▷ We need $\Delta >> |Q|$
    for each round $t \in B_\tau$ **do**
        if $h_\tau(p_i) = t$ for some price p_i **then**
            Use the estimator for price p_i and receive $\widehat{\mathrm{GFT}}_\tau(p_i)$
        else: Post price p_τ and ignore feedback
    Feed to $\mathcal{E}$ the estimated gains $\{\widehat{\mathrm{GFT}}_\tau(p_i)\}_i$

Theorem 5 (Upper bound on 2-regret given one bit feedback and posting two prices)**.** *In one bit-feedback model where the learner is allowed to post two prices, the* 2*-regret of* BLOCK-DECOMPOSITION *(*BD*) is such that* $R_T^2(\mathrm{BD}) \leq 5T^{3/4}\sqrt{\log(T)}$*, for appropriate choices of the expert algorithm* $\mathcal{E}$*, grid* Q *and number of blocks* S*.*

4.3 Lower bound on 2-regret, posting two prices and two bit feedback

We complement the positive results for the one-price and two bit feedback settings with a lower bound on the 2-regret achievable in the (easier) two price and two bit feedback setting. This lower bound strongly depends on the powerful characterization results from the partial monitoring literature [Bartók et al., 2014] and consists in constructing a class of instances with the following structure that mimic an "hard" partial monitoring game. The $[0, 1]$ interval is divided into 4 disjoint intervals, the first interval is composed by a single optimal price $p^\star$, then two intervals that are candidate to be the second best after $p^\star$. The only way for the learner to actually discriminate between the two candidates and assess which is the actual second best is to post prices in the last, suboptimal interval. The construction is such that there is a multiplicative factor 2 between the gain from trade of $p^\star$ and that of the second best. For the learner it is impossible to locate the single point $p^\star$ (recall the structure of the feedback), and its regret with respect to the second best prices is at least $\Omega(T^{2/3})$. The reader familiar with the learning literature would recognize the similarity of this structure to the classical revealing action problem [Cesa-Bianchi et al., 2006], that has also been used in Cesa-Bianchi et al. [2021a]. All in all, we show the following Theorem, whose proof is deferred to the appendix.

Theorem 6 (Lower bound on regret for two prices and two bit feedback)**.** *In the two bit feedback model where the learner is allowed to post two prices, for all horizons* $T \in \mathbb{N}$*, the minimax* 2*-regret satisfies* $R_T^{2,\star} \geq \tilde{c}T^{2/3}$ *for some constant* $\tilde{c}$*.*

5 Discussion, Extensions, and Open Problems

In this paper, we study the sequential bilateral trade problem with adversarial valuations. We study various feedback scenarios and consider the possibility for the mechanism to post one price vs. when it can post different prices for buyer and seller. We identify the exact threshold of α that allows sublinear α-regret. We show that with a partial feedback it is impossible to achieve sublinear α-regret for any constant α with a single price while 2-regret is achievable with 2 prices. Finally, we show a separation in the minimax 2-regret between full and partial feedback. Although in this paper we only consider the gain from trade, our positive results trivially also hold with respect to social welfare. Furthemore, modifying our lower bound from Theorem 1 it is possible to show that sublinear α-regret is not achievable for $\alpha < 2$ with respect to social welfare. An obvious open problem, with respect to both gain from trade and to social welfare, consists in determining the exact regret term as a function of T. Clearly there is a gap in our Table of results, and the exact term is yet unclear also for social welfare. We focus on the sequential problem where at each step one buyer and one seller appears. It would be interesting to study the model where multiple buyers and multiple sellers arrive at each time step and sellers have values for their goods, buyers have values for the different goods.

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Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes] All the claims are supported by formal statements and proofs either in the main body or appendix
   (b) Did you describe the limitations of your work? [Yes] For each result we state the conditions under which it holds.
   (c) Did you discuss any potential negative societal impacts of your work? [No] Our work is primarily theoretical and we do not foresee any potential negative societal impacts of our work.
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
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3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [N/A]
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(a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]

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