A Multi-Dimensional Auction Mechanism for Mobile Crowdsourced Video Streaming

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Abstract—Adaptive bitrate video streaming is a widely-used technology for mobile video streaming over HTTP. In this work, we study a crowdsourced video streaming framework, which enables nearby mobile users to crowdsource their radio resources for cooperatively adaptive bitrate video streaming. We propose a multi-dimensional auction based incentive mechanism to promote the user cooperation, supporting the asynchronous downloading and the bitrate adapting of video users. In this mechanism, each user initiates an auction whenever he is ready to download a new data segment in an asynchronous fashion, and all nearby users compete for the downloading opportunity by submitting a multi-dimensional bid consisting of the intended segment bitrate and the associated value. Design of such a multi-dimensional auction is very challenging, as we need to guarantee the user’s truthful reporting on the information on multiple dependent dimensions. We first propose a truthful second-score (multi-dimensional) auction framework, within which we further derive the efficient mechanism that maximizes the social welfare (of each segment downloading) and the sub-optimal mechanism that approximately maximizes the auctioneer payoff. Experiment results show that our proposed crowdsourced streaming can achieve 60% ~ 76% of the maximum social welfare even when 80 percentage of users lose their direct network connections.

I. INTRODUCTION

A. Background

Mobile video traffic is growing at an unprecedented rate, and is expected to increase 13-fold between 2014 and 2019, accounting for 72% of global mobile data traffic by 2019 [1]. Adaptive bitrate (ABR) video streaming [2] is a widely-used technology for video streaming over large distributed HTTP networks such as Internet. With the ABR technique, a source video is encoded at multiple bitrates (corresponding to different video qualities such as resolutions), and each bitrate stream is partitioned into a sequence of small multi-second parts, called segments. Mobile video users can adapt their playing bitrates to real-time network conditions, by choosing segments with proper bitrates. Such a rate adaptation is particularly important for mobile video streaming, due to limited network resources and high variations of wireless networks.

While most of the existing literature on ABR focused on the bitrate adaptation of a single user [3]–[6], we consider in this work a more general multi-user cooperative video streaming model. In the multi-user streaming model, the quality of experience (QoE) of each video user is affected not only by his own network condition (such as wireless channel fading), but also by the resource competition and interference of other users [7]. Hence, traditional bitrate adaptation methods [3]–[6] for single-user streaming model may fail to provide a desirable QoE for multiple video users, due to the lack of considerations of the potential network congestion and radio interference among users. In this work, we will study the user cooperation and the associated incentive mechanism for the multi-user streaming on wireless networks.

B. Motivations

In particular, we propose a novel user cooperation framework based on the crowdsourced user-provided networking (UPN) technology for multi-user streaming, called crowdsourced (video) streaming. The key idea is to enable nearby video users to form a cooperative group (via WiFi or Bluetooth) and crowdsource their radio connections and resources for video streaming. Namely, in a cooperative group, each user can download video data for others using his radio connection as well as get video data from others’ radio connections. Figure 1 illustrates such a crowdsourced network, where users 1 and 2 download three segments for user 3 who has no available Internet connection, and user 1 further downloads two segments for user 2 to enhance the QoE of user 2.

There are several advantages of applying such a crowdsourced UPN for multi-user video streaming. First, mobile users are highly heterogeneous in terms of their Internet access capabilities. Hence, crowdsourcing (aggregating) the throughput of neighbouring users can effectively reduce the network variation [8], [9]. Second, by exploiting the user diversity in radio resource availabilities and service requirements, such a crowdsourced UPN can reduce the negative externality (e.g., congestion and interference), while amplifying the positive network effect (e.g., diversity gain) [10]–[12]. Moreover, such a crowdsourced streaming can be easily implemented...
in practice by simply installing some customized apps (e.g., OpenGarden [13]) on smartphones.

Clearly, the success of such a crowdsourced streaming requires a proper incentive mechanism that encourages video users to crowdsource their radio resources and download data cooperatively. Some recent literatures [14] have considered the incentive issue in crowdsourced UPNs with elastic data applications. However, the incentive techniques in [14] cannot be directly applied to the crowdsourced streaming model, mainly because of the multi-bitrate requirement of video streaming and asynchronous operation of video segment downloading.

C. Solution and Contributions

In this work, we focus on the incentive mechanism design for multi-user crowdsourced video streaming. Namely, we aim to design such a mechanism that offers enough compensation for each video user to download data for others, considering his own service request and his downloading cost. With the ABR streaming, each video user downloads video segment by segment, i.e., he starts to download a new segment (either for himself or for another user) when completing a segment downloading. Hence, the proposed mechanism needs to consider the following problems for each user (downloader) when he is ready to download a new segment:

- **Receiver Selection**: Whose segment will he download?
- **Bitrate Adaptation**: What bitrate (quality) will the receiver choose for the segment to be downloaded?
- **Cost Compensation**: How much will he be compensated for his downloading cost by the receiver?

Addressing these problems is challenging due to the information asymmetry among users: each user has private information such as the personal preference for video service, which cannot be directly observed by others (see Section III-C).

To solve the above problems under information asymmetry, we propose a multi-dimensional auction [15]–[17] based incentive mechanism for multi-user crowdsourced video streaming. Specifically, a multi-dimensional auction (or multi-attribute auction) enables bidders to reveal more comprehensive information regarding the auctioned goods. Hence, the multi-dimensional auction model generalizes the single-dimensional model, and is applicable in a wider application scenario, e.g., financial markets, power procurement, and tourism industry [24], [25]. In our model, the key elements and features of the multi-dimensional auction are summarized below.

1) **Auctioneer (Downloader)**: When a user is ready to download a new segment, he acts as an auctioneer and initiates a multi-dimensional auction to those nearby users who are connected to him through Wi-Fi or Bluetooth. The multi-dimensional auction consists of (i) a winner selection policy, determining the receiver (winner) of the segment, and (ii) a payment policy, determining the receiver’s payment.

2) **Bidder (Potential Receiver)**: When a user observes an auction initiated by a nearby downloader, he acts as a bidder and submits a two-dimensional bid, which consists of (i) the intended bitrate of the video segment to be downloaded, and (ii) the value of the intended bitrate for him (or equivalently, the price he is willing to pay for the bitrate).

There are several unique features and challenges for such a multi-dimensional auction design. First, the bid is multi-dimensional, that is, a bidder needs to decide not only the price (value), but also the intended bitrate. Second, each user’s value for a particular bitrate (quality) is related not only to his private valuation information (i.e., his personal preference for video service), but also to his state information (e.g., his previously received bitrate and his current buffer level). It is important to note that such an auction-based mechanism does not require a real auction market. Instead, this mechanism can be programmed in the devices and work automatically.

In this work, we study the multi-dimensional auction design systematically under both complete and incomplete state information scenarios, depending on whether the auctioneer can observe the state information of bidders. Specifically, in each scenario, we first propose a truthful multi-dimensional auction framework, under which each user will submit the truthful bid (in the sense that the user’s reported value equals his true value). Within this truthful framework, we then derive the efficient auction that maximizes the social welfare, and the sub-optimal auction that maximizes the auctioneer’s profit approximately.

To our best, this is the first work that systematically studies the incentive issue in a crowdsourced video streaming framework for multi-user video streaming system. The key contributions are summarized as follows.

- **Auction-based Incentive Mechanism**: We propose a multi-dimensional auction based incentive mechanism for crowdsourced video streaming, supporting the asynchronous downloading and bitrate adapting of video users. Design of a multi-dimensional auction is challenging, as it needs to guarantee the user’s truthful reporting of value and the proper choice of bitrate.
- **Truthfulness and Efficiency**: We propose a truthful second-score (multi-dimensional) auction framework, within which we further propose the efficient and sub-optimal mechanisms that maximize the social welfare and auctioneer profit (approximately), respectively.
- **Experiments and Performances**: We construct experiments to illustrate the auction outcomes under different practical scenarios, corresponding to different percentages of disconnected users and different percentages of non-service users. Experiment results show that the crowdsourced streaming achieve 60% ∼ 76% of the maximum social welfare even when 80 percentage of users lose their direct network connections.

The rest of the paper is organized as follows. In Section III, we present the system model. In Sections IV, we propose the multi-dimensional auction. We present the simulation results in Section V, and finally conclude in Section VI.

II. LITERATURE REVIEW

A. Adaptive Bitrate Streaming

Prior works on adaptive video streaming mainly focused on the bitrate adaptation of a single user, and proposed different
adaptation methods (see [3] for a comprehensive discussion), including the buffer based method [4], the channel prediction based method [5], and the hybrid buffer and prediction based method [6]. Some recent works extended the basic single-user model to more advanced ones, such as multi-server model [18] and P2P model [19]–[23], and studied the associated incentive issues. In [18], Tian et al. considered the multi-server model, where clients download video from multiple servers to reduce the server load. In [19]–[23], researchers constructed adaptive streaming models on P2P systems to reduce the server load, and studied related incentive mechanisms for promoting the user cooperation in the P2P streaming. Although the P2P model considers the video sharing, the shared video is restricted to the videos that have been already downloaded by users. In the crowdsourced video streaming model, users can watch different video streaming simultaneously through cooperative downloading.

B. Multi-Dimensional Auction

Multi-dimensional auction (or multi-attribute auction) enables bidders to reveal more comprehensive information regarding the auctioned goods. In [15] and [16], Che and Asker et al. proposed the framework and general properties of multi-dimensional auction, based on which David et al. further analysed the auction properties under specific score functions in [17]. The multi-dimensional auction model generalizes the single-dimensional model, and is applicable in a wider application scenario, e.g., financial markets, power procurement, and tourism industry [24], [25].

To our best knowledge, this is the first work that adopts the multi-dimensional auction in adaptive streaming, by allowing bidders to report multiple necessary information such as bitrate and price. Due to the unique features of adaptive streaming, the multi-dimensional auction design in our model needs to consider not only the private valuation information of bidders, but also the state information of bidders. Such a consideration makes our auction design quite different and more challenging than the traditional multi-dimensional auction design.

III. SYSTEM MODEL

A. Adaptive Bitrate Streaming Model

We consider a set \( N \triangleq \{1, 2, ..., N\} \) of mobile video users, each watching an adaptive bitrate (ABR) streaming video on smartphone over 3G/4G cellular connections. Different users may watch different videos from different video servers. We consider a typical adaptive bitrate streaming model [2], where a single source video file is partitioned into multiple segments and delivered to a video user using HTTP. The key features of our streaming model are summarized below.

1) Video Segmenting: To facilitate the video delivery over the Internet, a source video file (e.g., a movie which is possibly several hours in duration) is divided into a sequence of small HTTP-based file segments, each corresponding to a short playback time (e.g., 2–10 seconds) of the source video. Moreover, users download videos segment by segment.

2) Multi-Bitrate Encoding: Each segment is encoded at multiple bitrates, corresponding different qualities (e.g., resolutions). Users can select the most suitable one from the candidate bitrates for each segment, according to factors such as real time network conditions and individual preferences.

3) Data Buffering: To smooth the playback, each downloaded segment is saved in a video buffer at the user’s device. The video player fetches segments from the buffer sequentially for playback. Due to the device memory’s limit, the maximum buffer size is usually limited (e.g., corresponding to 20–40 seconds of playback time).

Notations: Key notations in this part are listed below.

- \( \beta_n > 0 \): segment length (in seconds) of user \( n \)'s video;
- \( \mathcal{R}_n \triangleq \{R_{n}^{1}, R_{n}^{2}, ..., R_{n}^{Z}\} \) (with \( 0 < R_{n}^{1} < R_{n}^{2} < ... < R_{n}^{Z} \)): the set of bitrates (Mbps) available for user \( n \);
- \( B_n > 0 \): maximum buffer size (in seconds) of user \( n \).

Without loss of generality, we assume a unit segment length for all users’ videos, i.e., \( \beta_n = 1 \) second, \( \forall n \in \mathcal{N} \).

B. Crowdsourced Network Model

Mobile users are highly heterogeneous in terms of their video quality requirements and cellular link capacities. For example, a user playing a high (or low) quality video may happen to experience a low (high) cellular link capacity. Hence, it is desirable to enable users to crowdsource their cellular links for cooperative video downloading. We propose a crowdsourced UPN based cooperation framework, called crowdsourced streaming. In this framework, multiple users, who may watch different videos, form a cooperative group and download video segments for each other (as shown in figure 1). Namely, each user can download videos for the others as well as obtain videos downloaded by others; within the group, users forward the videos to the others directly via WiFi or Bluetooth connections. In this model, we assume that the video transmissions between the users are fast enough, so that we can ignore the interference that caused by simultaneous WiFi or Bluetooth transmissions.

Notations: We consider a continuous time model, and focus on the user operations over a period of time \( T \triangleq [0, T] \), where \( t = 0 \) is the initial time and \( t = T \) is the ending time. The key notations in this part are listed below.

- \( h_n(t) > 0 \): cellular link capacity of user \( n \) at time \( t \);
- \( e_{n,m}(t) \in \{0, 1\} \): whether users \( n \) and \( m \) are encountered (i.e., in the same location with \( e_{n,m}(t) = 1 \)) at time \( t \). Only encountered users can cooperate with each other.

C. User Model

Now we define the cost of user when downloading video data and the utility of user when receiving video data.

Without loss of generality, we consider the scenario where user \( n \) (downloader) downloads a segment of bitrate \( r \in \mathcal{R}_n \) for user \( m \) (receiver) at time \( t_0 \). The downloader \( n \) and receiver \( m \) can be the same user. Let \( T_n(r, t_0) \) denote the total time
of user $n$ for completing a segment downloading with size $r \cdot \beta_m = r$ (Mbits) starting at time $t_0$, i.e.,
\[
\int_{t_0}^{t_0+T_n(r,t_0)} h_n(t) dt = r.
\]

1) Cost of Downloader (User $n$): The cost of downloader mainly includes the energy cost (on both cellular link and local WiFi link) and the potential cellular data payment.

Let $E_n^{\text{CELL}}(r)$ denote the energy cost on cellular link, $E_n^{\text{WIFI}}(r)$ denote the energy cost on WiFi link (if $n \neq m$), and $G_n^{\text{CELL}}(r)$ denote the cellular data payment, for downloading a segment of bitrate $r$ for user $m$. Then, the total cost of user $n$ for downloading a segment of bitrate $r$ for user $m$ is:
\[
C_n(r) \triangleq E_n^{\text{CELL}}(r) + E_n^{\text{WIFI}}(r) + G_n^{\text{CELL}}(r).
\]

Note that $E_n^{\text{CELL}}(r)$, $E_n^{\text{WIFI}}(r)$, and $G_n^{\text{CELL}}(r)$ are all increasing functions of $r$. More specifically, these functions also depend on the starting time $t_0$ and the receiver $m$. Here we omit $t_0$ and $m$ for notational clarity.

2) Utility of Receiver (User $m$): The utility of receiver captures the user’s QoE of the video streaming service. Users often desire a higher video quality without frequent quality changes and freezes during playback. Hence, the user’s QoE or utility mainly depends on the following factors [3]–[6]: video quality, quality fluctuation, and rebuffering.

(a) Video Quality: A higher video bitrate (quality) can bring a higher value for users. Moreover, a user who is more desired for service can achieve a larger value from the same bitrate. We introduce a user-associated evaluation factor $\theta_m$ to capture the user $m$’s desire for video. Then, the value that user $m$ achieves from a (one-second) segment of bitrate $r$ can be defined as an increasing function $V_m(r, \theta_m)$ of $r$ and $\theta_m$. In this work, we adopt the following widely-used value function [7]:
\[
V_m(r, \theta_m) \triangleq \log(1 + \theta_m \cdot r).
\]

(b) Quality Fluctuation: The change of bitrate (quality) during playback decreases the user’s QoE, especially when the quality is degraded. In this work, we assume that there is a value loss that is proportional to the bitrate decrease, while there is no value loss when the quality is upgraded [7]. Let $R_{\text{PRE}}^m$ denote the bitrate of the previous received segment of user $m$, and $\phi_m^{\text{QDEG}}$ denote the value loss of user $m$ for one unit (in Mbps) of bitrate decrease. Then, the value loss of user $m$ that induced by quality degradation is
\[
L_m^{\text{QDEG}}(r, R_{\text{PRE}}^m) \triangleq \phi_m^{\text{QDEG}} \cdot [R_{\text{PRE}}^m - r]^+,
\]
where $[x]^+ = \max\{0, x\}$.

(c) Rebuffering: If a video buffer is exhausted before receiving a new segment, the video player has to freeze the playback and rebuffer the video for a certain time. Such a freezing during playback is called rebuffering. The rebuffering (freezing) during playback greatly affects the user’s QoE. We denote $B_{\text{CUR}}^m$ as the buffer level (in seconds) of user $m$ at time $t_0$. Obviously, a rebuffering occurs if $B_{\text{CUR}}^m < T_n(r, t_0)$, and the rebuffering time is $T_n(r, t_0) - B_{\text{CUR}}^m$. Let $\phi_m^{\text{REBUF}}$ denote the value loss of user $m$ for one unit (in seconds) of rebuffering time. Then, the value loss induced by rebuffering is
\[
L_m^{\text{REBUF}}(r, B_{\text{CUR}}^m) \triangleq \phi_m^{\text{REBUF}} \cdot [T_n(r, t_0) - B_{\text{CUR}}^m]^+.
\]

Based on the above, we can derive the utility of user $m$ for a new segment of bitrate $r$ as:
\[
U_m(r) \triangleq V_m(r, \theta_m) - L_m^{\text{QDEG}}(r, R_{\text{PRE}}^m) - L_m^{\text{REBUF}}(r, B_{\text{CUR}}^m). \tag{5}
\]

By (5), we can see that the utility of user $m$ is related not only to the user-associated evaluation factor $\theta_m$, but also to the user’s previous received bitrate $R_{\text{PRE}}^m$ and the current buffer level $B_{\text{CUR}}^m$. We refer to $\theta_m$ as the private valuation information of user $m$, which cannot be observed by other users. Moreover, we refer to $(R_{\text{PRE}}^m, B_{\text{CUR}}^m)$ as the state information of user $m$, which may or may not be observed by other users in different state information scenarios.

3) Social Welfare: The welfare generated through a single segment downloading (by downloader $n$ for receiver $m$) is the difference between receiver $m$’s utility and downloader $n$’s cost, i.e.,
\[
W_{nm}(r) = U_m(r) - C_n(r). \tag{6}
\]

Obviously, the welfare for each segment depends on the downloader $n$’s link capacity $h_n(t)$ in time $t \in [t_0, t_0 + T_n(r, t_0)]$ and the receiver $m$’s state information $(R_{\text{PRE}}^m, B_{\text{CUR}}^m)$ at time $t_0$. The total social welfare is the summation of the welfare generated through the downloading of all segments.

D. Problem Formulation

We are interested in the following problems in a multi-user crowdsourced video streaming model: at each decision epoch of user $n$ (i.e., at the time that a user completes a segment downloading and is ready for the next segment downloading), (i) for whom he is going to download the next segment, (ii) what is the bitrate of the target segment, and (iii) what is the payment from the segment receiver?

Solving these problems is challenging due to the private valuation information of receivers (i.e., $\theta_m$, $m \in \mathcal{N}$), which calls for incentive compatible mechanisms (e.g., auctions). In what follows, we will study the incentive mechanisms under two different state information scenarios: complete and incomplete state information, depending on whether the state information of a user is observable to others.

IV. AUCTION-BASED INCENTIVE MECHANISM

In this section, we propose a multi-dimensional auction-based incentive framework for our crowdsourced streaming model. First, we will introduce the multi-dimensional auction for our model. Then, we will study the efficient and sub-optimal multi-dimensional auctions under both complete and incomplete state information scenarios.

A. Multi-Dimensional Auction

To handle information asymmetry among users, we adopt an auction-based incentive framework for the crowdsourced streaming. The key idea is as follows. At each decision epoch of a user (who acts as a downloader for downloading a new segment), he initiates an auction (hence acts as an auctioneer) for all nearby users to decide the next segment to be downloaded. This framework operates in an asynchronous and

3 Strictly, the utility of user $m$ also depends on who is the downloader (i.e., $n$) and at what time the downloader starts to download (i.e., $t_0$).
decentralized manner, as different users download segments at different times.

In a particular auction, the auctioneer needs to determine not only the receiver and the payment (as in traditional auctions), but also the bitrate of the receiver’s segment to be downloaded. Moreover, the bitrate must be indicated by each bidder, as each user’s individual preference for bitrate is his private information. To this end, we adopt a multi-dimensional auction [15]–[17], where each bidder submits both the price and the intended segment bitrate.

1) Multi-Dimensional Auction Mechanism: Without loss of generality, we consider an auction initiated by a downloader $n$ at time $t_0$ for a set of encountered users:4

$$\mathcal{N}_n \triangleq \{m \in \mathcal{N} | e_{n,m}(t) = 1, t \in [t_0, t_0 + \epsilon]\}.$$

Note that the downloader $n$ is also in $\mathcal{N}_n$ as $e_{n,n}(t) = 1$. Intuitively, the downloader has his own service requirement, and will join the auction as a virtual bidder.5 Let $\theta$ (or $\theta_m$) denote the private valuation information of an arbitrary user (or user $m \in \mathcal{N}_n$). Let $\mu \triangleq (R^{PRE}, B^{CUR})$ (or $\mu_m \triangleq (R^{PRE}, B^{CUR})$) denote the state information of an arbitrary user (or user $m \in \mathcal{N}_n$). Let $\beta \triangleq (r,p)$ (or $\beta_m \triangleq (r_m,p_m)$) denote the two-dimensional bid of an arbitrary user (or user $m \in \mathcal{N}_n$). Formally, the multi-dimensional auction operates as follows.

**Mechanism 1 (Multi-Dimensional Auction Mechanism).**

1) The auctioneer (downloader) $n$ announces the winning rule $\Gamma(\cdot)$ and the payment rule $\Pi(\cdot)$ of the auction;

2) Each bidder $m \in \mathcal{N}_n$ submits a two-dimensional bid $\beta_m$, aiming at maximizing his expected payoff;

3) The auctioneer $n$ determines the receiver $m^\dagger$ and payment $p^\dagger$ according to the announced rules:

$$m^\dagger = \Gamma(\beta_m, m \in \mathcal{N}_n), \quad p^\dagger = \Pi(\beta_m, m \in \mathcal{N}_n).$$

Accordingly, the bitrate of the (receiver’s) segment to be downloaded is: $r^\dagger = r_{m^\dagger}$.

Given an auction outcome $(m^\dagger, p^\dagger, r^\dagger)$, the payoff of the auctioneer $n$ is

$$P_n(p^\dagger, r^\dagger) = p^\dagger - C_n(r^\dagger),$$

and the payoff of the receiver (winner) $m^\dagger$ is

$$P_{m^\dagger}(p^\dagger, r^\dagger) = U_{m^\dagger}(r^\dagger) - p^\dagger,$$

where $C_n(r^\dagger)$ is the downloader’s cost defined in (1), and $U_{m^\dagger}(r^\dagger)$ is the receiver’s utility defined in (5).

2) Score Function: The winning rule $\Gamma(\cdot)$ and payment rule $\Pi(\cdot)$ are two key elements in auction design. In a single-dimensional auction, the auctioneer can determine the winner by simply sorting all bidders’ prices and choosing the bidder with the highest price. In a multi-dimensional auction, however, the auctioneer cannot determine the winner by simply choosing the bidder with the highest price. This is because the bitrate of bidder will affect the auctioneer’s downloading cost, and hence the auctioneer’s payoff.

To this end, we introduce the score function in [16] to determine the winner and payment. The key idea is to transform a multi-dimensional bid $\beta = (r,p)$ into a single score $S(r,p)$, so that the auctioneer can sort bidders with their scores and determine the winner by choosing the highest score bidder. In this work, we adopt the additive score function [17].

**Definition 1 (Additive Score Function).** A score function $S(r,p)$ is additively separable, if

$$S(r,p) = p - s(r),$$

where $s(r)$ is an increasing function of $r$, and satisfies that $U_m(r) - s(r)$ has a unique interior maximum in $r$, $\forall m \in \mathcal{N}_n$.6

Intuitively, such a score function increases with the bidder’s price and decreases with the bidder’s bitrate, capturing the fact that the auctioneer prefers a higher price and a lower bitrate. Later we will show that by designing the score function or the function $s(\cdot)$ properly, we can achieve desirable outcomes such as efficient and sub-optimal ones.

**B. Auction under Incomplete State Information**

We first study the multi-dimensional auction design under incomplete state information scenario, where the auctioneer cannot observe the state information $\mu_m = (R^{PRE}, B^{CUR})$ of bidders $m \in \mathcal{N}_n$. Hence, the auctioneer will adopt the same score function to all bidders $m \in \mathcal{N}_n$:

$$S(r,p) = p - s(r).$$

In what follows, we propose a truthful multi-dimensional auction called second-score auction. Within this truthful second-score auction framework, we further propose two different score functions: (i) an efficient score function that maximizes the social welfare and (ii) an sub-optimal score function that maximizes the auctioneer’s payoff approximately.

1) Second-Score (Multi-Dimensional) Auction: Inspired by the second-price auction (single-dimensional), we propose a second-score auction (multi-dimensional), where the winner is the bidder with the highest score, and the winner’s payment is the price that derives the second highest score under the winner’s bitrate. Intuitively, the second-score auction can be viewed as a multi-dimensional extension of the second-price auction in the bidding structure.

**Mechanism 2 (Second-Score Auction under Incomplete State Information).** The second-score auction under incomplete state information is defined by:

1) Winning Rule: The winner $m^\dagger$ is the bidder with the highest score, i.e.,

$$m^\dagger = \arg\max_{m \in \mathcal{N}_n} S(r_m, p_m);$$

2) Payment Rule: The winner’s payment $p^\dagger$ is the price that derives the second highest score under his bitrate $r^\dagger = r_{m^\dagger}$, i.e.,

$$p^\dagger = s(r^\dagger) + \max_{m \in \mathcal{N}_n, m \neq m^\dagger} S(r_m, p_m).$$

6The requirement of “unique interior maximum” is used to ensure that each bidder can derive a unique best bidding strategy (in Proposition 2).
Proposition 1 (Truthfulness). Given any bitrate bidding strategy \( r_m \), the optimal price bidding strategy \( p_m \) of each bidder \( m \) is his true utility under the selected bitrate \( r_m \), i.e.,
\[
p_m = U_m(r_m).
\]

Proposition 2 (Optimal Bitrate Selection). The optimal bitrate bidding strategy \( r_m \) of each bidder \( m \) is given by
\[
r_m = \arg \max_{r \in \mathbb{R}_m} U_m(r) - s(r).
\]

Proposition 3 (Efficiency). The following score function
\[
S(r, p) \triangleq p - C_n(r)
\]
implies the efficient mechanism (that maximizes the social welfare), where \( C_n(r) \) is the downloading cost in (1).

Proposition 4 (Sub-Optimality in General Case). With a proper choice of \( k_0 \), the following score function
\[
S(r, p) \triangleq p - C_n(r) - k_0 \cdot r,
\]
implies a sub-optimal mechanism (that approximately maximizes the auctioneer’s payoff).

Specifically, we use a linear function \( k_0 \cdot r \) to approximate \( \Delta(r, \mu) \) in (14). Obviously, \( k_0 = 0 \) corresponds to the efficient score function in (13). Coefficient \( k_0 \) is a design parameter. In practice, an auctioneer can choose a proper \( k_0 \) based on empirical experiments.

C. Auction under Complete State Information

We now study the multi-dimensional auction design with complete state information, where the auctioneer can observe the state information \( \mu_m = (P_m^{\text{PRE}}, B_m^{\text{CUR}}) \) of each bidder \( m \in \mathcal{N}_m \). Note that \( \theta_m \) is still the private information of bidder \( m \) and cannot be observed by others. In this case, the auctioneer can adopt a distinct score function to each bidder \( m \):
\[
S_m(r, p) = p - s_m(r),
\]
depending on the bidder’s state information \( (R^{\text{PRE}}_m, B^{\text{CUR}}_m) \). Hence, two bidders with the same bid may have different scores, due to the different state information.

Similar as in the incomplete information scenario, we first propose a truthful second-score multi-dimensional auction, and then study the efficient and sub-optimal score functions.

Mechanism 3 (Second-Score Auction under Complete State Information). The second-score auction under complete state information is defined by:

- Winning Rule:
  \[
  m^\dagger = \arg \max_{m \in \mathcal{N}_n} S_m(r_m, p_m);
  \]
- Payment:
  \[
  p^\dagger = s_m(r^\dagger) + \max_{m \in \mathcal{N}_m/m^\dagger} S_m(r_m, p_m).
  \]

The key difference between Mechanisms 2 and 3 is that in the former case, all bidders’ bids are evaluated by the same score function \( S(r, p) \), while in the latter case, each bidder \( m \)’s bid is evaluated by a distinct score function \( S_m(r, p) \).

Proposition 5 (Truthfulness). Given any bitrate bidding strategy \( r_m \), the optimal price bidding strategy \( p_m \) of each bidder \( m \) is his true utility under the selected bitrate \( r_m \), i.e.,
\[
p_m = U_m(r_m).
\]

Proposition 6 (Optimal Bitrate Selection). The optimal bitrate bidding strategy \( r_m \) of each bidder \( m \) is given by
\[
r_m = \arg \max_{r \in \mathbb{R}_m} U_m(r) - s_m(r).
\]

Proposition 7 (Efficiency). The following score function set
\[
S_m(r, p) \triangleq p - C_n(r), \quad \forall m \in \mathcal{N}_n
\]
implies the efficient mechanism (that maximizes the social welfare), where \( C_n(r) \) is the downloading cost in (1).

Proposition 8 (Sub-Optimality). With proper choices of \( \{k_m, m \in \mathcal{N}_n\} \), the following score function set
\[
S_m(r, p) \triangleq p - C_n(r) - k_m \cdot r, \quad \forall m \in \mathcal{N}_n
\]
implies a sub-optimal mechanism (that approximately maximizes the auctioneer’s payoff).

It is easy to see that the efficient score functions in Proposition 7 are identical for all users, and equivalent to the efficient score function (13) in Proposition 3 for the incomplete
state information scenario. Similarly, \( \{k_m, m \in \mathcal{N}_n\} \) in Proposition 8 are design parameters and can be chosen via empirical experiments in practice, as \( k_0 \) in Proposition 4.

V. EXPERIMENTS AND PERFORMANCE

A. Experiment Setting

1) Real-World Datasets: We apply real data traces in experiments to simulate cellular link capacities. The link capacity trace is obtained from bestTV\(^7\), one of the largest over-the-top video service providers in China. In this dataset, around 28\% users experience a throughput lower than 1Mbps; around 50\% users experience a throughput lower than 2.5Mbps; and around 85\% users experience a throughput lower than 5.0Mbps.

2) Experiment Setting: The experiments are constructed in a simultaneous online video streaming system with 50 users and 5 locations, in a period of 50 seconds (within which each user attempts to watch a 50-second video). Each user randomly selects a location at the beginning of each experiment, hence each location has 10 users on average. According to the data from bestTV, video streaming is encoded with bitrate \( \{0.2, 0.4, 0.7, 1.3, 2.3\} \text{Mbps} \). The segment length is 1 second for all videos, and the buffer length is 20 seconds for all users. In each experiment, we randomly generate 100 systems (in terms of link capacities and user locations), and compute the average outcome as the experiment result.

3) Performance Metrics: We will study two performance metrics: social welfare and downloader payoff, under different cooperative schemes: (i) non-cooperative (Non) benchmark, where users do not cooperate, and download their own segments independently; (ii) partially cooperative (Partial) benchmark, where users form fixed cooperative groups (5 users per group), and download video for his own or his partners within the group (when encountered); (iii) fully cooperative (Full) with efficient mechanism (Full-E) and sub-optimal mechanism (Full-S), where users fully and dynamically cooperate with each other, and help all encountered users based on the efficient mechanism and sub-optimal mechanism, respectively.

We construct experiments to simulate two practical scenarios: Scenario A, where some users are disconnected, hence can only get data from others; Scenario B, where some users are not playing video, hence have more resources to help others. In Scenario A, we fix the total number of users, and gradually increase the ratio of disconnected users. In Scenario B, we fix the number of users with video services, and gradually add additional users without video services.

\(^7\)Detailed data can be found at http://www.bestv.com.cn/

B. Social Welfare

Figure 2 (a) shows the social welfare vs. the disconnected user percentage (Scenario A). In this figure, the social welfare decreases with the disconnected user percentage under all four schemes, while the decrease is less dramatic under Full-E and Full-S than other two benchmark schemes. Specifically, under non-cooperative benchmark, social welfare reduces approximately 88.8\% as the disconnected user percentage increases from 0\% to 80\%, while the reduction is about 40.2\% under Full-E, and 24.4\% under Full-S. Moreover, Full-S is even better than Full-E when the disconnected user percentage is large. The reason is that the sub-optimal mechanism that used in Full-S trends to reduce the bitrate, hence benefits more disconnected users, leading to a larger social welfare\(^8\). In summary, cooperation benefits the social welfare when some users are disconnected, and the benefit increases with the percentage of disconnected users.

Figure 2 (b) shows the social welfare vs. the no video service user percentage (Scenario B). It shows that the social welfare slightly increases with the no service user percentage under three cooperative schemes (Partial, Full-E, and Full-S), but does not change under non-cooperative benchmark, because the users without video services can help others in the three cooperative schemes with the higher effort. Moreover, Full-E and Full-S are better than Partial, while the performance gain decreases with the no service user percentage.

C. Downloader’s Payoff

Downloader’s payoff is the user’s payoff from downloading for the others. Figure 3 (a) shows the downloader’s payoff vs. the disconnected user percentage (Scenario A) under partially and fully cooperative schemes.\(^9\) We can see that the downloader’s payoff increases with the disconnected user percentage, due to the increased demand (from disconnected users) and decreased competition. Moreover, the increase is much larger under Full-E and Full-S than under Partial; in other words, only full cooperative schemes can fully benefit the connected users who can serve as downloaders.

Figure 3 (b) shows the downloader payoff vs. the no service user percentage (Scenario B) under partially and fully cooperative schemes. In this figure, the downloader’s payoff decreases with the no service user percentage under Full-E and

\(^8\)Note that we have proved the Full-E maximizes the social welfare in a single segment downloading. However, in Figure 2 we are showing the social welfare for the entire time period (50 seconds).

\(^9\)We ignore the non-cooperative scheme, because there is no user helping others, hence no downloader payoff.
VI. CONCLUSION

In this work, we studied a crowdsourced video streaming framework, which enables nearby mobile users to crowdsource their radio resources and cooperate with each other for joint video streaming. We proposed a multi-dimensional auction based incentive mechanism, and analyzed the truthfulness, efficiency, and optimality of the proposed auction mechanisms systematically under different state information scenarios. There are several interesting directions for extending this work. First, it is meaningful to study the optimal multi-dimensional auction analytically in the general case. Second, it is interesting to study a more general scenario, where bidders make decisions based on not only the current state information, but also the prediction of future states. Our study in this work provides an important first step towards these extensions.

REFERENCES


APPENDIX

A. Proof for Proposition 1

Given any bitrate \( r_m \), the score that the bidder obtains only depends on the price that the bidder submits, i.e., \( S(r_m,p) = p - s(r_m) \), and \( s(r_m) \) becomes a constant. Hence, the price truthfulness is equivalent to the score truthfulness under the given bitrate. The second-score auction is a VCG mechanism in terms of the score, so we have the score truthfulness (resulting in the price truthfulness).

B. Proof for Proposition 2

We aim to show that for any bid \( (r_m, p) \), there always exists a bid \( (r_m, p^\ast) \) such that it has larger expected payoff than \( (r_m, p') \) does, where \( r_m \) is given in Proposition 2 and \( S(r_m, p^\ast) = S(r_m, p) \). Specifically, bids \( (r_m, p^\ast) \) and \( (r', p') \) have the same winning probability, because they share the same score. When lose, both of them get zero payoff; when win, \( (r_m, p^\ast) \) has a larger payoff, i.e.,

\[
U_m(r_m) - (\hat{S} + s(r_m)) \geq U(r_m) - (\hat{S} + s(r'_m)),
\]

where \( \hat{S} \) denotes the second highest score, because \( r_m = \arg\max_{r_m} U_m(r) - s(r) \) under the constraints.

C. Proof for Proposition 3

According to Proposition 1 and Proposition 2, bidder \( m \) submits bid \( (r_m, p_m) \), where \( r_m = \arg\max_{r_m} U_m(r) - C_n(r) \) and \( p_m = U_m(r_m) \). Then the score for bidder \( m \) is:

\[
S(r_m, p_m) = \max_{r \in [r_m]} U_m(r) - C_n(r).
\]

In second-score auction, bidder with the highest score wins. The winner and the bitrate result are as follows:

\[
\{r^\ast, m^\ast\} = \arg\max_{r \in [r_m], m \in N_n} U_m(r) - C_n(r).
\]

This implies that the auction result \( \{r^\ast, m^\ast\} \) maximizes the social welfare.

D. Proof for Proposition 5 to 7

In complete state information, the bidders still aim to maximize their expected payoff based on the given distinct score function. Hence, the proof for Proposition 5 (truthful) and Proposition 6 (optimal bitrate selection) are the same as the proof for Proposition 1 and Proposition 2 respectively.

Furthermore, the efficient score functions are the same for all the bidders, i.e., \( S_m(r, p) = p - C_n(r) \). Under the same score function, this problem degrades to incomplete state information case. Similarly, the score that bidder \( m \) submits is given by:

\[
S_m(r_m, p_m) = \max_{r \in [r_m]} U_m(r) - C_n(r).
\]

In second-score auction, bidder with the highest score wins. The winner and the bitrate result are as follows:

\[
\{r^\ast, m^\ast\} = \arg\max_{r \in [r_m], m \in N_n} U_m(r) - C_n(r).
\]

This implies that the auction result \( \{r^\ast, m^\ast\} \) maximizes the social welfare. Proposition 7 proved.