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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 $60\% \sim 76\%$ 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.

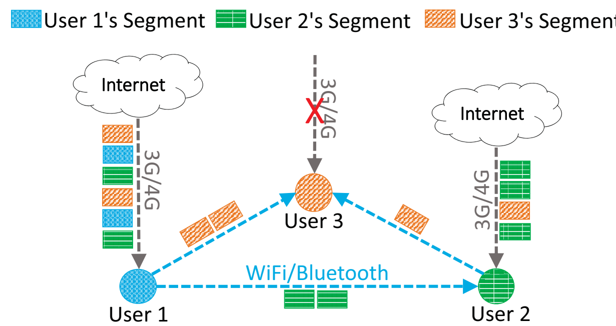

Fig. 1. Crowdsourced Video Streaming Model.

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].[1] Moreover, such a crowdsourced streaming can be easily implemented

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[1] As a result, crowdsourced UPN has already some successes in commercial applications, such as FON [10] (a crowdsourced WiFi community network in UK) and Karma [11] (a UPN-based mobile virtual network in USA).

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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 Adaption:* 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).[2] 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 $60\% \sim 76\%$ 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

[2]Please refer to Section III-C for more detailed discussions regarding the private valuation information and the state information.

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 $\mathcal{N} \triangleq \{1, 2, ..., N\}$ 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 $\mathcal{T} \triangleq [0,\ T]$, 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 $r \in \mathcal{R}_m$ 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.,

$$\int_{t_0}^{t_0+T_n(r,t_0)} h_n(t)\mathrm{d}t = r.$$

*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:

$$C_n(r) \triangleq E_n^{\text{CELL}}(r) + E_n^{\text{WIFI}}(r) + G_n^{\text{CELL}}(r). \tag{1}$$

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 θ_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 θ_m. In this work, we adopt the following widely-used value function [7]:

$$V_m(r, \theta_m) \triangleq \log(1 + \theta_m \cdot r). \tag{2}$$

(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_m^{PRE} denote the bitrate of the previous received segment of user m, and ϕ_m^{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

$$L_m^{\text{QDEG}}(r, R_m^{\text{PRE}}) \triangleq \phi_m^{\text{QDEG}} \cdot \left[R_m^{\text{PRE}} - r\right]^+, \tag{3}$$

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_m^{CUR} as the buffer level (in seconds) of user m at time t_0. Obviously, a rebuffering occurs if $B_m^{\text{CUR}} < T_n(r, t_0)$, and the rebuffering time is $T_n(r, t_0) - B_m^{\text{CUR}}$. Let ϕ_m^{REBUF} denote the value loss of user m for one unit (in seconds) of rebuffering time. Then, the value loss induced by rebuffering is

$$L_m^{\text{REBUF}}(r, B_m^{\text{CUR}}) \triangleq \phi_m^{\text{REBUF}} \cdot \left[T_n(r, t_0) - B_m^{\text{CUR}}\right]^+. \tag{4}$$

Based on the above, we can derive the *utility* of user m for a new segment of bitrate r as:[3]

$$U_m(r) \triangleq V_m(r, \theta_m) - L_m^{\text{QDEG}}(r, R_m^{\text{PRE}}) - L_m^{\text{REBUF}}(r, B_m^{\text{CUR}}). \tag{5}$$

By (5), we can see that the utility of user m is related not only to the user-associated evaluation factor θ_m, but also to the user's previous received bitrate R_m^{PRE} and the current buffer level B_m^{CUR}. We refer to θ_m as the **private valuation information** of user m, which can not be observed by other users. Moreover, we refer to $(R_m^{\text{PRE}}, B_m^{\text{CUR}})$ 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 $(R_m^{\text{PRE}}, B_m^{\text{CUR}})$ 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]

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

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 θ (or θ_m) denote the private valuation information of an arbitrary user (or user $m \in \mathcal{N}_n$). Let $\boldsymbol{\mu} \triangleq (R^{\text{PRE}}, B^{\text{CUR}})$ (or $\boldsymbol{\mu}_m \triangleq (R_m^{\text{PRE}}, B_m^{\text{CUR}})$) denote the state information of an arbitrary user (or user $m \in \mathcal{N}_n$). Let $\boldsymbol{\beta} \triangleq (r, p)$ (or $\boldsymbol{\beta}_m \triangleq (r_m, p_m)$) 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* $\boldsymbol{\beta}_m$*, aiming at maximizing his expected payoff;*
3) *The auctioneer* n *determines the receiver* $m^\dagger$ *and payment* $p^\dagger$ *according to the announced rules:*
$$m^\dagger = \Gamma(\boldsymbol{\beta}_m,\ m \in \mathcal{N}_n), \quad p^\dagger = \Pi(\boldsymbol{\beta}_m,\ m \in \mathcal{N}_n).$$
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

$$P_n(p^\dagger, r^\dagger) = p^\dagger - C_n(r^\dagger), \tag{7}$$

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

$$P_{m^\dagger}(p^\dagger, r^\dagger) = U_{m^\dagger}(r^\dagger) - p^\dagger, \tag{8}$$

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.

[4]Here ϵ is a small positive value capturing the maximum possible downloading time of the downloader n for any encountered user's segment.

[5]The downloader's own bid can be viewed as a *reserve bid*, determining the minimum bid with which he is willing to download for other users.

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 $\boldsymbol{\beta} = (r, p)$ 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*

$$S(r, p) = p - s(r), \tag{9}$$

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 $\boldsymbol{\mu}_m = (R_m^{\text{PRE}}, B_m^{\text{CUR}})$ of bidders $m \in \mathcal{N}_n$. Hence, the auctioneer will adopt the same score function to all bidders $m \in \mathcal{N}_n$:

$$S(r, p) = p - s(r). \tag{10}$$

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

[6]The requirement of "unique interior maximum" is used to ensure that each bidder can derive a unique best bidding strategy (in Proposition 2).

2) Truthfulness: Now we show that the proposed second-score auction is truthful, in the sense that each bidder will reveal the true valuation under any bitrate selection.

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.,*

$$p_m = U_m(r_m). \tag{11}$$

Proposition 2 (Optimal Bitrate Selection)**.** *The optimal bitrate bidding strategy r_m of each bidder m is given by*

$$r_m = \arg\max_{r \in \mathcal{R}_m} \; U_m(r) - s(r). \tag{12}$$

Propositions 1 and 2 characterize the optimal bidding strategy of each bidder m in the second-score auction. Intuitively, each bidder will select the bitrate that maximizes the difference between utility and increasing function $s(r)$, and select the price that equals the true utility under the selected bitrate.

By Proposition 2, we can further see that the bitrate selection of each bidder depends on the auctioneer's score function. Hence, *the auctioneer can carefully design the score function* (10) *to achieve different desirable auction outcomes.*

3) Efficient Score Function: A score function $S(r,p)$ is efficient if it maximizes the expected social welfare:

$$\mathbb{E}_{\theta,\boldsymbol{\mu}} \; \left[U_{m^\dagger}(r^\dagger) - C_n(r^\dagger) \right].$$

Here, $m^\dagger$ and $r^\dagger$ are the auction outcome (i.e., winner and bitrate) under a particular realization of θ and $\boldsymbol{\mu}$. Note that the payment $p^\dagger$ is cancelled out in the social welfare. The expectation is taken over all possible realizations of all bidders' private valuation information θ and state information $\boldsymbol{\mu}$.

Proposition 3 (Efficiency)**.** *The following score function*

$$S(r,p) \triangleq p - C_n(r) \tag{13}$$

implements the efficient mechanism (that maximizes the social welfare), where $C_n(r)$ is the downloading cost in (1)*.*

4) Optimal Score Function: A score function $S(r,p)$ is optimal if it maximizes auctioneer's expected payoff:

$$\mathbb{E}_{\theta,\boldsymbol{\mu}} \; \left[p^\dagger - C_n(r^\dagger) \right].$$

In general, however, it is challenging to solve the optimal score function, due to the complicated relationship between payment $p^\dagger$ and information realization $(\theta, \boldsymbol{\mu})$.

We first consider a special case, where all users have the same state information: $\boldsymbol{\mu}_m = \boldsymbol{\mu}$, $\forall n \in \mathcal{N}_n$. In this special case, we can derive the optimal score function based on [15]. The optimal score function formulation is given as follows:

$$S(r,p) \triangleq p - C_n(r) - \Delta(r, \boldsymbol{\mu}), \tag{14}$$

where $\Delta(r,\boldsymbol{\mu})$ is a function of r and $\boldsymbol{\mu}$. Through numerical results, we find that $\Delta(r,\boldsymbol{\mu})$ increases near linearly with r in our model. This inspires us to propose a *sub-optimal* score function in general case.

Proposition 4 (Sub-Optimality in General Case)**.** *With a proper choice of k_0, the following score function*

$$S(r,p) \triangleq p - C_n(r) - k_0 \cdot r, \tag{15}$$

implements a sub-optimal mechanism (that approximately maximizes the auctioneer's payoff).

Specifically, we use a linear function $k_0 \cdot r$ to approximate $\Delta(r,\boldsymbol{\mu})$ 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 $\boldsymbol{\mu}_m = (R_m^{\text{PRE}}, B_m^{\text{CUR}})$ of each bidder $m \in \mathcal{N}_n$. Note that θ_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 $(R_m^{\text{PRE}}, B_m^{\text{CUR}})$. 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 Informaiton)**.** *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*:*
$$p^\dagger = s_{m^\dagger}(r^\dagger) + \max_{m \in \mathcal{N}_n / m^\dagger} S_m(r_m, p_m).$$

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.,*

$$p_m = U_m(r_m). \tag{16}$$

Proposition 6 (Optimal Bitrate Selection)**.** *The optimal bitrate bidding strategy r_m of each bidder m is given by*

$$r_m = \arg\max_{r \in \mathcal{R}_m} \; U_m(r) - s_m(r). \tag{17}$$

Proposition 7 (Efficiency)**.** *The following score function set*

$$S_m(r,p) \triangleq p - C_n(r), \quad \forall m \in \mathcal{N}_n \tag{18}$$

implements 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*

$$S_m(r,p) \triangleq p - C_n(r) - k_m \cdot r, \quad \forall m \in \mathcal{N}_n, \tag{19}$$

implements 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

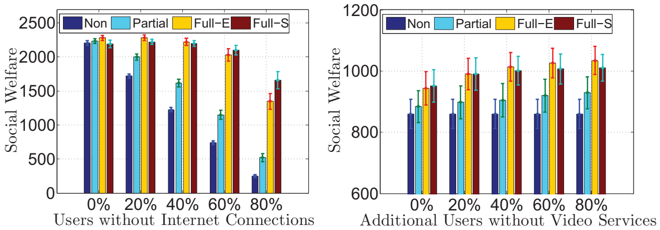

Fig. 2. Social Welfare under Scenario A and Scenario B.

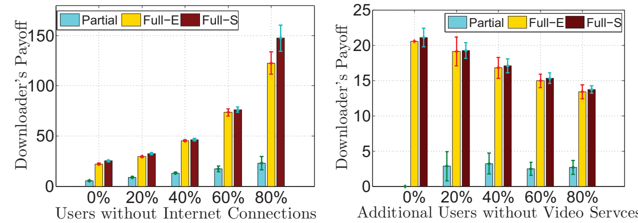

Fig. 3. Downloader's Payoff under Scenario A and Scenario B.

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 simulative 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 $\{0.2,\ 0.4,\ 0.7,\ 1.3,\ 2.3\}$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.

Full-S, due to the decreased demand and increased competition (from no service users).

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.

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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^*) such that it has larger expected payoff than (r'_m, p') does, where r_m is given in Proposition 2 and $S(r'_m, p') = S(r_m, p^*)$. Specifically, bids (r_m, p^*) and (r'_m, 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^*) has a larger payoff, i.e.,

$$U_m(r_m) - \underbrace{(\widehat{S} + s(r_m))}_{payment} \geq U(r'_m) - \underbrace{(\widehat{S} + s(r'_m))}_{payment},$$

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

C. Proof for Proposition 3

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

$$S(r_m, p_m) = \max_{r \in \mathcal{R}_m} U_m(r) - C_n(r). \tag{20}$$

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

$$\{r^\dagger, m^\dagger\} = \arg \max_{r \in \mathcal{R}_m, m \in \mathcal{N}_n} U_m(r) - C_n(r). \tag{21}$$

This implies that the auction result $\{r^\dagger, m^\dagger\}$ 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:

$$S_m(r_m, p_m) = \max_{r \in \mathcal{R}_m} U_m(r) - C_n(r). \tag{22}$$

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

$$\{r^\dagger, m^\dagger\} = \arg \max_{r \in \mathcal{R}_m, m \in \mathcal{N}_n} U_m(r) - C_n(r). \tag{23}$$

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