Near-Optimal Truthful Spectrum Auction Mechanisms With Spatial and Temporal Reuse in Wireless Networks

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ABSTRACT

In this work, we study spectrum auction problem where each spectrum usage request has spatial, temporal, and spectral features. After receiving bid requests from secondary users, and possibly reserve price from primary users, our goal is to design truthful mechanisms that will either optimize the social efficiency or optimize the revenue of the primary user. As computing an optimal conflict-free spectrum allocation is an NP-hard problem, in this work, we design near optimal spectrum allocation mechanisms separately based on the techniques: derandomized allocation from integer programming formulation, and its linear programming (LP) relaxation. We theoretically prove that 1) our derandomized allocation methods are monotone, thus, implying truthful auction mechanisms; 2) our derandomized allocation methods can achieve a social efficiency or a revenue that is at least $1 - \frac{1}{e}$ times of the optimal respectively; Our extensive simulation results corroborate our theoretical analysis.

Categories and Subject Descriptors

C.2.1 [**Computer Systems Organization**]: Computer Communication Networks; D.2.8 [**Management of Computing and Information Systems**]: Installation Management—*Pricing and resource allocation*

Keywords

Spectrum auction; Truthful; Approximation mechanism; Social efficiency; revenue

1. INTRODUCTION

The growing demand for limited spectrum resource poses a great challenge in spectrum allocation and usage. One of the most promising methods is spectrum auction, which provides sufficient incentive for primary user (*a.k.a seller*) to sublease spectrum to secondary users (*a.k.a buyers*). The design of spectrum auction mechanisms are facing two major challenges. First, spectrum channels can be reused in spatial, temporal, and spectral domain if the buyers are conflict-free with each other, and thus, allocating the requests of buyers in channels optimally is often an NP-hard problem. Second, truthfulness is regarded as one of the most critical properties, however, it's difficult to ensure truthfulness in a spectrum auction mechanism with performance guarantee. Recent years, many mechanisms were proposed to address some of the auction challenges [1–3, 7–11]. However, to the best of our knowledge, there is no truthful spectrum auction mechanism with performance guarantee, in which spectrums can be reused both in spatial and temporal domains.

Maximization of the ***social efficiency***, *i.e.* allocating a channel to buyers who **value** it most, and maximization of the ***expected revenue***, *i.e.* allocating a channel to buyers who **pay** it most, both are the natural goals for spectrum auctions. Thus, we design a framework for spectrum auction which can maximize the social efficiency or the expected revenue. Since channels can be reused in both spatial and temporal domain, the problem of allocating requests of buyers in channels optimally to maximize the social efficiency or the expected revenue is NP-hard. To tackle this challenge, we first relax the integer programming formulation of the channel allocation problem into a linear program (LP) problem, which is solvable in polynomial time. A fractional solution for channel allocation can be obtained by solving this LP optimally. Then, we transform this fractional solution into a feasible integer solution of the original channel allocation problem by using a carefully designed randomized rounding procedure that ensures the feasibility of the solution and good approximation to the objective functions. We prove that the **expected** weight of the feasible integer solution is at least $1 - 1/e$ times of the weight of the optimal solution. To complete our allocation mechanism, we also propose a derandomization algorithm to get a feasible solution whose weight is always guaranteed to be at least $1 - 1/e$ times of the weight of the optimal solution. Then, we propose a revised derandomization algorithm and prove that this new allocation method does satisfy the bid-monotone property, thus, implying a truthful mechanism. We point out that our allocation mechanisms can either approximate the social efficiency or the expected revenue, but not both simultaneously.

2. PRELIMINARIES

Auctions in our model are executed periodically. In each round, the primary user subleases the access right of m channels in the fixed areas during time interval $[0, T]$, and n buyers request the usage of channels in fixed time intervals and geographical location-

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s/areas. Our goal is to allocate these requests of buyers in channels, such that we maximize either the social efficiency or the expected revenue. We consider two models of the requests of buyers. The first one is the *Point model*, in which each buyer requests the usage of channels in a particular geographical location and during a fixed time interval. The second one is *Area model*, in which each buyer requests the usage of channels in a particular geographical area and also during a fixed time interval.

We use $\mathcal{S}$ to denote the set of channels, and define each channel $s_j \in \mathcal{S}$ as $s_j = (R_j, A_j)$, where A_j is its license area, and R_j is the interference radius of a transmission when a user transmits in channel s_j. Let $\mathcal{B}$ be the set of buyers, in which each buyer $i \in \mathcal{B}$ is assumed to have a request r_i. Let $\mathcal{R}$ be the set of requests of buyers. Each request $r_i \in \mathcal{R}$ is defined as $r_i = (L_i, b_i, v_i, a_i, t_i, d_i)$, where L_i is i's geographical location in *Point model* or the area where i wants to access the channel in the *Area model*, b_i denotes its bidding price, v_i stands for its true valuation, and a_i, d_i, and t_i denote the arrival time, deadline, and duration time (or time length), respectively. In this paper, we only consider the case of $d_i - a_i = t_i$, which means that the time request from the buyer is a fixed time interval. We leave the case of $d_i - a_i > t_i$ as the future work.

We say that two requests r_i and r_k conflict with each other, if they satisfy the following constrains: (1) The distance between L_i and L_k is smaller than twice of the interference radius in the *Point model*, or $L_i \bigcap L_k \neq \emptyset$ in the *Area model*; and (2) The required time intervals from r_i and r_k overlap with each other. We denote the conflict relationships among requests by a conflict graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where $\mathcal{V}$ is the set of requests of buyers, and edge $(r_i, r_k) \in \mathcal{E}$ if requests r_i and r_k conflict with each other. Note that, for the same requests r_i and r_k, different interference radii of channels will lead to a different conflict relationship. We use a matrix $Y = (y_{i,k,j})_{n\times n\times m}$ to represent the conflict relationships in graph $\mathcal{G}$, in which if requests r_i and r_k conflict with each other in channel s_j, $y_{i,k,j} = 1$; otherwise, $y_{i,k,j} = 0$. Since the spectrum is a local resource, we also need to define a location matrix $C = (c_{i,j})_{n\times m}$ to represent whether L_i is in the license regions of channel s_j. $c_{i,j} = 1$ if L_i is in the license regions of channel c_j; otherwise, $c_{i,j} = 0$. Therefore, two requests r_i and r_k can share channel s_j only if $y_{i,k,j} = 0$, and $c_{i,j} = 1$, $c_{k,j} = 1$.

The objective of our work is to design a mechanism satisfying *truthfulness* constraint, while maximizing the *social efficiency* or *revenue*. In our problem definition, an auction is said to be truthful if revealing true valuation is the *dominant strategy* for each bidder, regardless of other bidders' bids. An auction mechanism is truthful if its allocation algorithm is monotonic and it always charges critical values from its buyers [5]. The *critical value* for a buyer is the minimum bid value, with which the buyer will win the auction.

Social Efficiency Maximization: Social efficiency for an auction mechanism is defined as $\max \sum_{r_i\in\mathcal{R}} v_i x_i$, where $x_i = 1$ if buyer i wins in the auction; otherwise, $x_i = 0$.

Revenue Maximization: The revenue of an auction is the total payment of buyers. An auction maximizing the revenue for the auctioneer is known as an optimal auction in economic theory [4]. In the optimal auction, Myerson introduces the notion of virtual valuation $\phi_i(b_i)$ as

$$\phi_i(b_i) = b_i - \frac{1 - F_i(b_i)}{f_i(b_i)} \tag{1}$$

where $F_i(b_i)$ is the probability distribution function of true valuations of buyer i, and $f_i(b_i) = \frac{dF_i(b_i)}{db_i}$. According to the theory of optimal auction [4], maximizing the expected revenue is equivalent to finding the optimal solution of $\max \sum_{r_i\in\mathcal{R}} \phi_i(b_i) x_i$.

3. A STRATEGYPROOF SPECTRUM AUCTION FRAMEWORK

In this section, we propose a general truthful spectrum auction framework with the goal of maximizing social efficiency or revenue, as shown in *Algorithm 1*. In our framework, we can flexibly choose different optimization targets according to the practical requirements of auction problems. To ensure the worst case profit, the primary user will set a virtual reservation price η^θ, which is the minimum virtual price for spectrums per unit time. Let $\{\xi\}_\Psi$ denote a set whose elements satisfy property Ψ. The details are depicted as follows.

Algorithm 1 Our truthful spectrum auction framework

Input: conflict graph $\mathcal{G}$, location matrix C, set of channels $\mathcal{S}$, set of requests $\mathcal{R}$, monotone allocation and payment mechanism $\mathcal{A}$;
Output: channel assignment X, payment P;
$\mathcal{R}' = \mathcal{R}$;
for each $r_i \in \mathcal{R}$ **do**
  if the target is maximization of social efficiency **then**
    $\phi_i(b_i) = b_i$;
  else
    $\phi_i(b_i) = b_i - \frac{1-F_i(b_i)}{f_i(b_i)}$;
  if $\phi_i(b_i) < \eta^\phi t_i$ **then**
    $\mathcal{R}' = \mathcal{R}' \backslash \{r_i\}$; // Delete r_i from set $\mathcal{R}'$
Run $\mathcal{A}$ using the set of virtual bids $\{\phi_i(b_i)\}_{r_i\in\mathcal{R}'}$;
Let $X = \{x_i\}_{r_i\in\mathcal{R}'}$ be the channel allocation and $\tilde{P} = \{\tilde{p_i}\}_{r_i\in\mathcal{R}'}$ be the corresponding payment returned by $\mathcal{A}$;
for each $x_i = 1$ **do**
  if the target is maximization of social efficiency **then**
    $p_i = \tilde{p}_i$;
  else
    $p_i = \phi_i^{-1}(\tilde{p_i})$;
return (X, P);

4. ALLOCATION MECHANISM WITH APPROXIMATION RATIO (1-1/e)

4.1 The Optimal Channel Allocation

In the channel allocation problem, we need to match the requests and channels optimally under their constraints. In order to simplify the matching model between requests and channels, we would like to segment the available time of each channel into many time slices. Recall that the available time of each channel is [0,T] in each auction period. Then, we use the arrival time a_i and deadline d_i of each request r_i to partition the time interval [0,T]. Each arrival time/deadline of requests divides the time axis of one channel into two parts. Suppose there are n requests, the time interval [0,T] is divided into no more than $2n + 1$ time slices.

After the introduction of segmentation process, we give the detailed description of the channel allocation problem. First, for each partitioned time slice derived from channel s_j, it can only be allocated to the requests within the license area of channel s_j. Let $x^l_{j,i}$ represent whether the *l-th* time slice of channel s_j is allocated to the request r_i, then we get a constraint $x^l_{j,i} \leq c_{i,j}$. Second, each time slice can only be allocated to requests conflict-free with each other. Thus, we get another constraint $\sum_{k\neq i} x^l_{j,k} y_{i,k,j} + x^l_{j,i} \leq 1$. Let t^l_j be the length of *l-th* time slice in channel s_j. Modify a_i to be the first time slice r_i wants to use, and d_i to be the last time slice r_i wants to use. Moreover, if we allocate request r_i in channel s_j, the time assigned to request r_i from channel s_j should be equal to the required time of request r_i, so we get $\sum_{l=a_i}^{d_i} x_{j,i}^l t_j^l = t_i x_{i,j}$. From the analysis above, the allocation problem can be formulated as follows.

$$\max \sum\nolimits_{s_j \in \mathcal{S}} \sum\nolimits_{r_i \in \mathcal{R}'} \phi_i(b_i) x_{i,j}, \textit{subject to}, \qquad \text{(IP (1))}$$

$$\begin{cases} \sum_{s_j \in \mathcal{S}} x_{i,j} \le 1, \forall r_i \in \mathcal{R}' \\ x_{j,i}^l \le c_{i,j}, \forall s_j \in \mathcal{S}, \forall r_i \in \mathcal{R}', \forall l \\ \sum_{k \ne i} x_{j,k}^l y_{i,k,j} + x_{j,i}^l \le 1, \forall s_j \in \mathcal{S}, \forall r_i \in \mathcal{R}', \forall l \\ \sum\limits_{l=a_i}^{d_i} x_{j,i}^l t_j^l = t_i x_{i,j}, \forall s_j \in \mathcal{S}, \forall r_i \in \mathcal{R}' \\ x_{i,j} \in \{0,1\}, \forall s_j \in \mathcal{S}, \forall r_i \in \mathcal{R}' \\ x_{j,i}^l \in \{0,1\}, \forall s_j \in \mathcal{S}, \forall r_i \in \mathcal{R}', \forall l \end{cases}$$

where $x_{i,j}$ stands for whether channel s_j is allocated to request r_i or not, $y_{i,k,j}$ represents whether request r_i conflicts with request r_k or not in channel s_j.

4.2 (1-1/e)-Approximation methods

LP relaxation technique can be introduced to solve NP-hard problems, and it often leads to a good approximation algorithm. We release IP(1) to linear programming LP(2) by replacing $x_{i,j} \in \{0,1\}$ with $0 \le x_{i,j} \le 1$, and replacing $x_{j,i}^l \in \{0,1\}$ with $0 \le x_{j,i}^l \le 1$.

Recall that the number of time slices is no more than $2n+1$ for each channel, so LP(2) has a polynomial number of variables and constraints, and can be solved optimally in polynomial time.

4.2.1 *Randomized Rounding*

Suppose O_{LP2} is the optimal solution of LP(2), we apply a standard randomized rounding on it to obtain an integral feasible solution f_{IP1} to IP (1). The rounding procedure is presented as follows.

1. Randomly choose a channel s_j, randomly choose a request r_i with $x_{i,j} > 0$, and set $x_{i,j} = 1$;
2. If $x_{i,j} = 1$, set $x_{k,j} = 0$ for all requests r_k with $y_{i,k,j} = 1$;
3. If $x_{i,j} = 1$, set $x_{i,k} = 0$ for all channels with $k \ne j$.
4. Repeat steps 1 to 3 until all requests have been processed.

Through the randomized rounding procedure above, the optimal solution of LP(2) is converted into a feasible solution of IP(1). Let $w_{O_{LP2}}$ be the weight of O_{LP2}, and let $E(w_{f_{IP1}})$ be the expected weight of f_{IP1}. We show in Theorem 1 that $E(w_{f_{IP1}}) \ge (1 - 1/e) w_{O_{LP2}}$.

THEOREM 1. *The expected weight of the rounded solution is at least* $1 - 1/e$ *times of the weight of the optimal solution to LP (2).*

PROOF. Due to the page limit, all the detailed proofs can be referred to [6]. □

We have shown that the expected weight of feasible solution f_{IP1} of IP (1) obtained by our randomized rounding is larger than $1 - 1/e$ times of the weight of the optimal solution of LP (2). Obviously, the weight of the optimal solution of LP (2), which is denoted by $w_{O_{LP2}}$, is larger than the optimal solution of IP (1), which is denoted by $w_{O_{IP1}}$. Therefore, we can get that

THEOREM 2. *The expected weight of the rounded solution is at least* $1 - 1/e$ *times of the weight of the optimal solution to IP (1).*

4.2.2 *Deterministic Methods*

The rounding procedure only makes sure that the expected weight of f_{IP1} is larger than $1 - 1/e$ times of the weight of O_{LP2}. What we need is to find a feasible solution of IP(1) whose weight is exactly larger than $1 - 1/e$ times of the $w_{O_{LP2}}$. In the following, we show that the rounding procedure can be derandomized and how the method of conditional probabilities can be used in our setting.

Algorithm 2 DCA: Derandomized Channel Allocation Based on Linear Programming

Input: Conflict graph $\mathcal{G}$, location matrix C, set of channels $\mathcal{S}$, set $\mathcal{R}'$ sorted in increasing order according to a_i;
Output: channel assignment X^* ;
Solve LP(2) optimally;
$E(w_{f_{IP1}}) = \sum\limits_{s_j \in \mathcal{S}} \phi_i(b_i)(1 - \prod_{s_j \in \mathcal{S}} (1 - x_{i,j}))$;
for $i = 1$ to n **do**
  if $x_i > 0$ **then**
    for $j = 1$ to m **do**
      if $E(w_{f_{IP1}}) \le E(w_{f_{IP1}} | i, j)$ **then**
        set $x_{i,j} = 1$, $x_i = 1$;
        set all $x_{i,k} = 0$ and $x_{i,k}^l = 0$ if $k \ne j$;
        set all $x_{k,j} = 0$ and $x_{k,j}^l = 0$ if $k \ne i$ and $y_{i,k,j} = 1$;
        Break
  if $x_i \ne 1$ **then**
    $x_i = 0$;
return X^*;

Let $E(w_{f_{IP1}} | r_i \to s_j)$ be the expected weight when request r_i is allocated in channel s_j, and let $E(w_{f_{IP1}} | \tilde{i})$ be the expected weight when request r_i will not be allocated in any channel. Next, we will show how our derandomization algorithm works. We first sort all the requests by their arrival time a_i in the ascending order. Let $x_i = \sum_{j \in \mathcal{S}} x_{i,j}$, and then scan all the requests one by one to decide which request can be allocated in channels. When request r_i is considered, we scan all of the channels that are available for r_i to check if r_i can be allocated in one of them. If $E(w_{f_{IP1}} | r_i \to s_j) < E(w_{f_{IP1}})$, set $x_{i,j} = 0$; otherwise, allocate r_i in channel s_j, and set $x_{i,j} = 1$, $x_i = 1$, $x_{i,k} = 0$ if $k \ne j$. Meanwhile, if r_i is allocated in channel s_j, we set $x_{k,j}^l = 0$ if $y_{i,k,j} = 1$.

Suppose r_i is the first request that satisfies $x_i > 0$ in the ordered requests. Let $q_{i,j}$ denote the probability that request r_i is allocated in channel s_j and let $q_{\tilde{i}}$ denote the probability that r_i is not allocated in any channel. By the formula for conditional probabilities, we have

$$E(w_{f_{IP1}}) = \sum_{r_j \in S} E(w_{f_{IP1}} | r_i \to s_j) q_{i,j} + E(w_{f_{IP1}} | \tilde{i}) q_{\tilde{i}} \quad (2)$$

In particular, there exists at least one conditional expectation in $E(w_{f_{IP1}} | r_i \to s_1), \cdots, E(w_{f_{IP1}} | r_i \to s_m), E(w_{f_{IP1}} | \tilde{i})$, which is larger than $E(w_{f_{IP1}})$. If it is $E(w_{f_{IP1}} | r_i \to s_j) \ge E(w_{f_{IP1}})$, we allocate request r_i in channel s_j; otherwise, $E(w_{f_{IP1}} | \tilde{i}) \ge E(w_{f_{IP1}})$ holds, reject request r_i, and set $x_{i,j} = 0$ for each $s_j \in \mathcal{S}$. This can be done since $E(w_{f_{IP1}}) = \sum_{r_i \in \mathcal{R}'} \phi_i(b_i) q_i$, and q_i can be computed precisely by

$$q_i = 1 - \prod_{s_j \in \mathcal{S}} (1 - x_{i,j}) \quad (3)$$

Let $q_{r_i \to s_j, k}$ stand for the probability that request r_k is allocated in a channel when request r_i is allocated in s_j. Then $q_{r_i \to s_j, k}$ can be calculated by

$$q_{r_i \to s_j, k} = \begin{cases} 1 - \prod_{o \ne j} (1 - x_{k,o}), y_{i,k,j} = 1 \\ q_k, otherwise \end{cases} \quad (4)$$

For each request r_i, we can compute $E(w_{f_{IP1}}|r_i \rightarrow s_j)$ precisely as the follows

$$E(w_{f_{IP1}}|r_i \rightarrow s_j) = \phi_i(b_i) + \sum\nolimits_{k \neq i} \phi_k(b_k) q_{r_i \rightarrow s_j, k} \quad (5)$$

Given the selections in the prior requests, we can continue deterministically to allocate other requests and do the same thing while maintaining the invariant that the conditional expectation $E(w_{f_{IP1}})$, never deceases. After allocating all of the requests, we can get a feasible solution of IP(1) whose weight is as good as $E(w_{f_{IP1}})$, *i.e.* at least $(1-1/e)w_{O_{LP2}}$.

Recall that to ensure the truthfulness of our auction mechanism, the allocation algorithm must be bid-monotone. However, we cannot prove or disprove the bid-monotone property of the allocation method DCA (presented in Algorithm 2). Thus, it is unknown whether we can design a truthful mechanism based on this method. In the rest of the section, we revise this method and show that the revised method does satisfy the bid-monotone property.

Since that there exists at least one of the conditional expectations between $max_{s_j \in \mathcal{S}} E(w_{f_{IP1}}|r_i \rightarrow s_j)$ and $E(w_{f_{IP1}}|\tilde{i})$, which is larger than $E(w_{f_{IP1}})$. Thus, if we allocate r_i in the channel with the maximal conditional expectation as long as $max_{s_j \in \mathcal{S}} E(w_{f_{IP1}}| r_i \rightarrow s_j) \geq E(w_{f_{IP1}}|\tilde{i})$, and do not allocate r_i in any channel otherwise, we can also get a feasible solution of IP(1), whose weight is as good as $E(w_{f_{IP1}})$.

This can be done since we can compute $E(w_{f_{IP1}}|i,j)$ and $E(w_{f_{IP1}}|\tilde{i})$ precisely as follows:

$$E(w_{f_{IP1}}|r_i \rightarrow s_j) = \phi_i(b_i) + E_{k \neq i}(w_{f'_{IP1}}|r_i \rightarrow s_j) \quad (6)$$

where $E_{k \neq i}(w_{f'_{IP1}}|r_i \rightarrow s_j)$ is the expected weight of all other requests when request r_i has been allocated in channel s_j. We can get it by allocating r_i in channel s_j first, and then solve LP(2) optimally with other requests.

$$E(w_{f_{IP1}}|\tilde{i}) = E_{\mathcal{R}'/r_i}(w_{f'_{IP1}}) \quad (7)$$

where $E_{\mathcal{R}/r_i}(w_{f'_{IP1}})$ is the expected weight of all other requests when request r_i is not allocated in any channel. We can get it by solving LP(2) optimally with requests except r_i.

Based on the observation above, we give a revised version (called MDCA) of Algorithm DCA as follows.

Algorithm 3 MDCA: Monotone Derandomized Channel Allocation Based on Linear Programming

Input: Conflict graph $\mathcal{G}$, location matrix C, set of channels $\mathcal{S}$, set of $\mathcal{R}'$ sorted in increasing order according to a_i;
Output: channel assignment X^* ;

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Solve LP(2) optimally;
for i = 1 to n do
    for j = 1 to m do
        if x_{i,j} > 0 then
            E(w_{f_{IP1}}|r_i → s_k) = max_{s_j∈S} E(w_{f_{IP1}}|r_i → s_j)
            if E(w_{f_{IP1}}|r_i → s_k) ≥ E(w_{f_{IP1}}|ĩ) then
                set x_{i,j} = 1, x_i = 1;
                set all x_{i,k} = 0 and x^l_{i,k} = 0 if k ≠ j;
                set all x_{k,j} = 0 and x^l_{k,j} = 0 if k ≠ i and y_{i,k,j} = 1;
                Break
    if x_i ≠ 1 then
        x_i = 0;
return X*;
```

In MDCA, we first sort all of the requests by their arrival times in the ascending order, and then we scan all requests one by one to decide which request can be allocated in channels. When request r_i is considered, we compute $E(w_{f_{IP1}}|r_i \rightarrow s_j)$ for all channels $s_j \in \mathcal{S}$ that no request conflicting with it has been allocated in. We allocate r_i in channel s_k when $E(w_{f_{IP1}}|r_i \rightarrow s_k) = max_{s_j \in \mathcal{S}} E(w_{f_{IP1}}|r_i \rightarrow s_j) \geq E(w_{f_{IP1}}|\tilde{i})$, and reject it otherwise. After the last request was considered in MDCA, we get a feasible solution of IP (1), whose weight is as good as $E(w_{f_{IP1}})$.

THEOREM 3. *MDCA (see Algorithm 3) is bid monotone.*

Since the revised Algorithm MDCA is bid-monotone, there exists a critical value for each winner. Thus, we can design a truthful auction mechanism through charging each winner its critical value.

5. CONCLUSION

In this paper, we have studied the case that spectrum can be reused spatial domain, temporal domain. We have designed a general truthful spectrum auction framework which can maximize the social efficiency or revenue. As allocating channels optimally is NP-hard in our model, we have also proposed a set of near-optimal channel allocation mechanisms with an approximation factor of $(1-1/e)$.

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