Optimal Design for Electricity Auctions: A Deep Learning Approach

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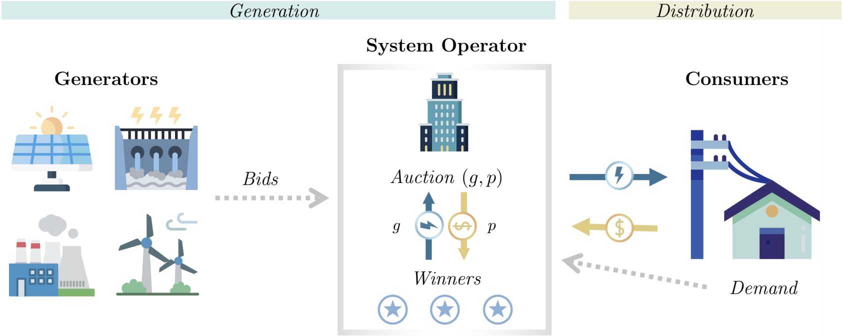
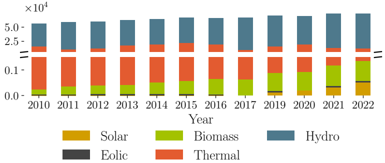
Electricity auctions



Colombian electricity market

- Main generation sources: hydro and thermal power

Generation (GWh)



- Concentrated generation capacity in a few firms
- Current design results in bids above true unitary costs (McRae and Wolak, 2017; Balat et al., 2023)
- Plans to diversify generation mix include (UPME, 2020):
  - Introducing solar and wind energy
  - Reducing thermal power due to environmental impact
  - Improving reliability during reduced rainfall periods

Design problem

Optimal auction design

- Strategy-proof auction:
  - Minimizes expected generation costs
  - Incentivizes participation and truthful bidding, procures demand and satisfies capacity constraints

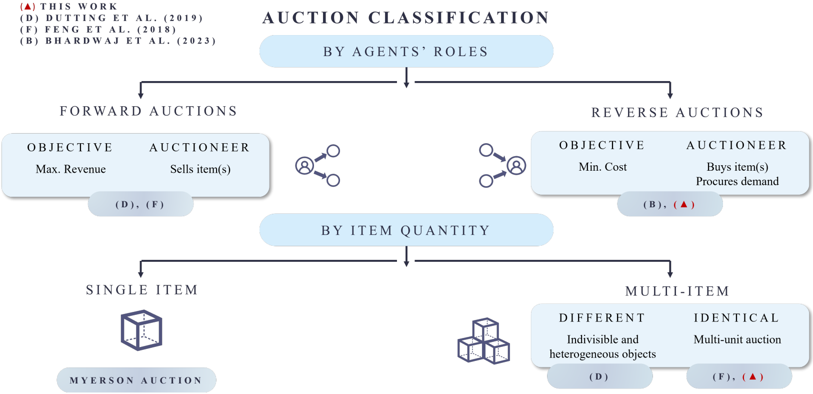
Challenges

- Technical considerations: uncertain capacity and demand, diverse generation technologies, correlated costs.
- Multiple competing objectives: Price stability, environmental sustainability, operation reliability, cost minimization.

Related work

Dutting et al.'s (2019) *RegretNet*

- Deep learning framework modeling auction rules as neural networks
- Structures the problem as a constrained learning problem
- Focuses on multi-item, revenue maximizing auctions.



This work

(1) Extends the *RegretNet* framework for electricity auctions

- Recovers analytical solutions with low approximation errors in cost levels ($< 1\%$) and low constraint violations (≤ 0.002).
- Discovers new results for (simplified) settings with: (1) uncertain capacity and demand, (2) correlated costs, (3) multiple time-slot bids

(2) Evaluates the effect in generation costs of integrating wind and solar power in Colombia using real data

- Expanding capacity and increasing the number of bidders reduces the expected cost.
- This reduction is slightly higher when wind and solar energy are integrated
- Integration of wind-solar energy reduces the incidence of extreme cost instances during reduced rainfall periods.

Optimal auction design problem

- n generators competing for d_j electricity units to produce at each time slot $j \in [m]$.
- Demand d_j is perfectly inelastic.
- Each generator has a (1) private unit cost v_i (same throughout the day) and (2) known capacities $\bar{q}_{ij}$ for each time slot j.
- Unit cost profiles $\boldsymbol{v} = (v_i)_{i \in [n]}$ drawn from $F = (F_i)_{i \in [n]}$, known by the system operator.
- Bidders submit a single unit price bid b_i for their entire generation.

Auction

- Given bidding profile $\boldsymbol{b} = (b_i)_{i \in [n]}$, an auction $(\boldsymbol{g}, \boldsymbol{p})$ is characterized by an allocation rule $\boldsymbol{g}$ and a payment rule $\boldsymbol{p}$.
- g_{ij}: number of units allocated for slot j. p_i: payment for energy produced
- Auctions can be modeled as parametric functions $\rightarrow$ NN with weights $\boldsymbol{w}$

Generators' profit

- Generator with unit cost v_i, under $(\boldsymbol{g}, \boldsymbol{p})$ bids b_i. Given $\boldsymbol{b} \in V$, profit is defined as

$$\pi_i(v_i, \boldsymbol{b}) = \begin{cases} p_i(\boldsymbol{b}) - C(\boldsymbol{g}_i(\boldsymbol{b}), v_i) & \text{if } g_{ij}(\boldsymbol{b}) \leq \bar{q}_{ij} \ \forall j \in [m] \\ -\infty & \text{otherwise.} \end{cases},$$

where $C(\boldsymbol{g}_i(\boldsymbol{b}), v_i) = \sum_{j=1}^{m} g_{ij}(\boldsymbol{b}) v_i$.

Optimal auction properties

- *Individually rational* (IR): Bidding truthfully results in a non-negative profit (within NN)

$$\pi_i(v_i, (v_i, \boldsymbol{b}_{-i})) \geq 0, \quad \forall i \in [n], v_i \in \mathcal{V}_i, \boldsymbol{b}_{-i} \in \mathcal{V}_{-i}.$$

- *Demand constraint* (DC): Procures demand (within NN)

$$\sum_{i=1}^{n} g_{ij}(\boldsymbol{b}) \geq d_j, \quad \forall j \in [m], \boldsymbol{b} \in \mathcal{V}.$$

- *Dominant strategy incentive compatible* (DSIC): Incentivizes generators to report their true unit costs → Regret (rgt) = 0 in the learning problem

$$\pi_i(v_i, (v_i, \boldsymbol{b}_{-i})) \geq \pi_i(v_i, (b_i, \boldsymbol{b}_{-i})), \quad \forall i \in [n], v_i \in \mathcal{V}_i, b_i \in \mathcal{V}_i, \boldsymbol{b}_{-i} \in \mathcal{V}_{-i},$$

where the zero regret condition is defined as

$$rgt_i(\boldsymbol{w}) = \mathbb{E}_{\boldsymbol{v}\sim F}\left[\max_{v_i' \in \mathcal{V}_i} \gamma \left(\pi_i^w(v_i, (v_i', \boldsymbol{v}_{-i})) - \pi_i^w(v_i, (v_i, \boldsymbol{v}_{-i}))\right)\right] = 0,$$

and $\gamma = \Pi_{j=1}^m \mathbb{1}\left(g_{ij}^w(v_i', \boldsymbol{v}_{-i}) \leq \bar{q}_{ij}\right)$.

- *Capacity constraint* (CC): Allocation rule assigns generators at most their capacity → Capacity constraint penalty (ccp) = 0 in the learning problem

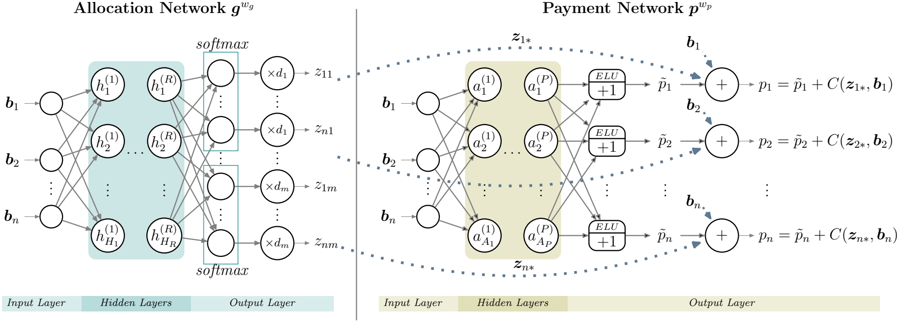
$$g_{ij}(\boldsymbol{b}) \leq \bar{q}_{ij}, \quad \forall i \in [n], j \in [m], \boldsymbol{b} \in \mathcal{V},$$

where zero capacity constraint penalty condition is defined as

$$ccp_i(\boldsymbol{w}) = \mathbb{E}_{\boldsymbol{v}\sim F}\left[\sum_{j=1}^m \max\left\{g_{ij}^w(\boldsymbol{v}) - \bar{q}_{ij}, 0\right\}\right] = 0, \quad \forall i \in [n].$$

Model architecture

Neural network for encoding procurement multi-unit auctions



$\tilde{p} \in [0, \infty)$ is the information rent

Learning problem

Minimize daily generation costs

$$\begin{aligned} \min_{\boldsymbol{w}\in\mathbb{R}^r} \quad & \mathbb{E}_{\boldsymbol{v}\sim F}\left[\sum_{i=1}^{n} p_i^w(\boldsymbol{v})\right] \\ \text{s.t.} \quad & rgt_i(\boldsymbol{w}) = 0, \quad ccp_i(\boldsymbol{w}) = 0, \quad \forall i \in [n] \end{aligned} \tag{1}$$

Augmented Lagrangian method Lift constraints by minimizing the following unconstrained loss function

$$\begin{aligned} \mathcal{L}_p(\boldsymbol{w},\boldsymbol{\lambda}) = \frac{1}{L}\sum_{\ell=1}^{L}\sum_{i=1}^{n} p_i^w(\boldsymbol{v}^{(\ell)}) + \sum_{i=1}^{n}\lambda_i^{rgt}\widehat{rgt}_i(\boldsymbol{w}) + \frac{\rho^{rgt}}{2}\sum_{i=1}^{n}\left(\widehat{rgt}_i(\boldsymbol{w})\right)^2 \\ + \sum_{i=1}^{n}\lambda_i^{ccp}\widehat{ccp}_i(\boldsymbol{w}) + \frac{\rho^{ccp}}{2}\sum_{i=1}^{n}\left(\widehat{ccp}_i(\boldsymbol{w})\right)^2 \end{aligned}$$

Analytical solution

For single time-slot settings ($m = 1$) problem (1) has an analytical solution (based on Iyengar and Kumar (2008); Chaturvedi (2015)). For $n = 2, v_i \sim U[0,1]$:

- Sequentially allocates units to generators with the lowest costs, exhausting their capacity or until demand is satisfied

$$g_i^*(\boldsymbol{v}) = \begin{cases} \min(d, \bar{q}_i) & \text{if } v_i < v_k \\ d - \min(d, \bar{q}_k) & \text{if } v_i > v_k \end{cases} \tag{2}$$

- Payment depends on production costs + the opportunity cost of misreporting (*information rent*)

$$p_i^*(\boldsymbol{v}) = \begin{cases} v_i g_i^*(\boldsymbol{v}) + (v_k - v_i) g_i^*(\boldsymbol{v}) + (1 - v_k)(d - \min(d, \bar{q}_k)) & \text{if } v_i < v_k \\ v_i g_i^*(\boldsymbol{v}) + (1 - v_i) g_i^*(\boldsymbol{v}) & \text{if } v_i > v_k \end{cases} \tag{3}$$

- No incentives to misreport capacity even if it is private (payments depend positively on capacities and profit is unbounded when CC are violated)

Single-slot experiments

Overall Perfomance

- Demand of 1. Unit costs independently drawn from $U[0,1]$. Constant capacities.

	Analytical sol.	*RegretNet*		
	cost	*cost*	*rgt*	*ccp*
Uncapacitated	0.6664	0.6691	<0.001	–
$\bar{\boldsymbol{q}} = (0.6, 0.6)$	0.9333	0.9318	0.001	<0.001
$\bar{\boldsymbol{q}} = (0.6, 0.8)$	0.8665	0.8693	<0.001	<0.001
$\bar{\boldsymbol{q}} = (0.3, 0.9)$	0.9333	0.9350	<0.001	<0.001
$\bar{\boldsymbol{q}} = (0.6, 0.4, 0.4)$	0.8002	0.7978	<0.001	<0.001

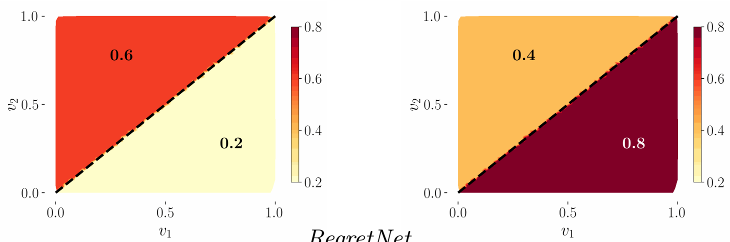
- Cost level errors $< 1\%$, low constraint violations (≤ 0.001)
- Increasing aggregate capacity $\Rightarrow$ Lower expected costs
- Distributing aggregate capacity among more generators $\Rightarrow$ Lower expected costs

Experiment: $\bar{q} = (0.6, 0.8)$

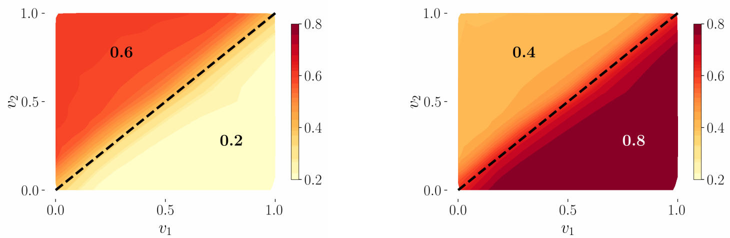
Allocation rule

Analytical solution

Generator 1 Generator 2

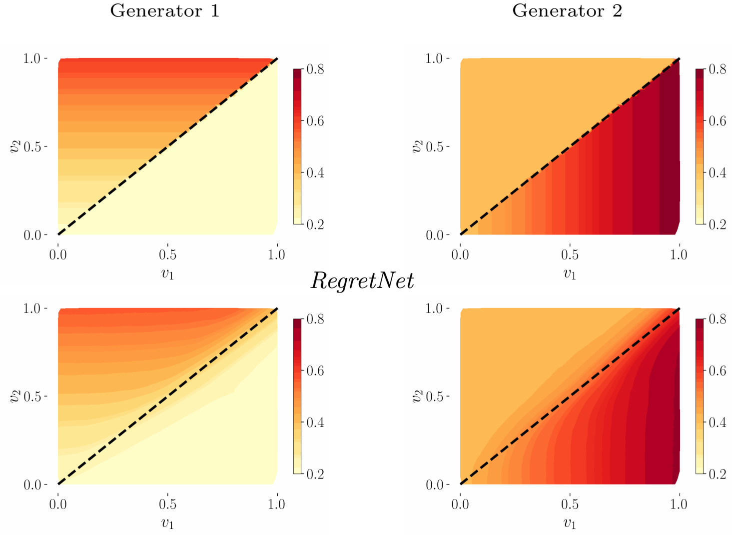


RegretNet



Payment rule

Analytical solution



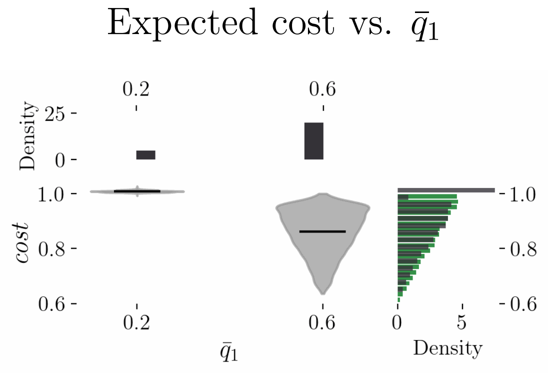
Uncertain capacity

(1) 2 generators: the first has capacity equal to 0.6 with 80% probability and 0.2 with 20%. The second has constant capacity of 0.8. Unit costs drawn from $U[0,1]$

(2) 3 generators: the first is a wind generator with capacity distributed Rayleigh(0.3) with unit costs drawn from $U[0,0.4]$. The second and third generators have capacity of 0.5 each with unit costs drawn from $U[0,1]$

		RegretNet		
$\bar{\boldsymbol{q}}$	d	*cost*	*rgt*	*ccp*
$v_i \sim U[0,1]$				
$\bar{q}_1 = 0.6x + 0.2(1-x), x \sim \text{Bernoulli}(0.8); \bar{q}_2 = 0.8$	1	0.8907	<0.001	<0.001
$v_1 \sim U[0,0.4]; v_2, v_3 \sim U[0,1]$				
$\bar{q}_1 \sim \text{Rayleigh}(0.3); \bar{q}_2, \bar{q}_3 = 0.5$	1	0.6770	<0.001	<0.001

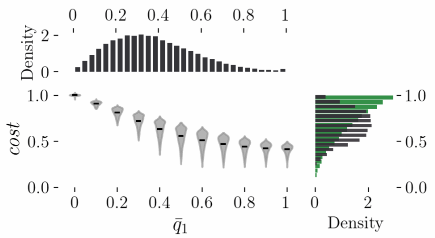
Uncertain capacity (Supply failure)



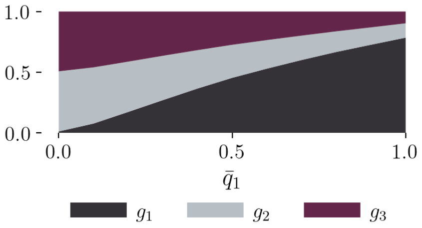
Supply failure risk

Uncertain capacity (Wind integration)

Expected cost vs. $\bar{q}_1$



Generation mix

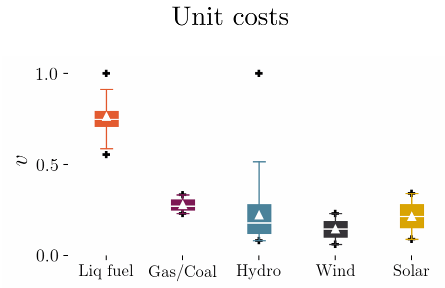


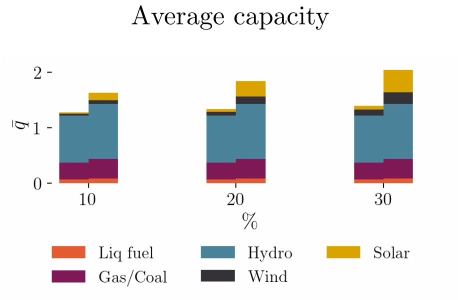
Real-data experiments

- Random demand and capacity
- 2 time slots:
  - Low demand slot (1°): 10pm-8am
  - High demand slot (2°): 9am-9pm
- Single daily unit cost for all slots
- 5 generators grouped by source:
  - Liquid-fueled thermoelectric
  - Gas/Coal thermoelectric
  - Hydro
  - Wind
  - Solar
- Unit costs: Input costs, VOM, taxes (liquid-fueled, gas/coal thermo), minimum between bid and price (hydro), LCOE (wind, solar)
- Capacities: Declared capacity (liquid-fueled thermo, gas/coal thermo, hydro), wind speed (wind) and solar irradiance (solar)
- Data was normalized and distributions were fitted

Real-data experiments

- Aggregate capacity was increased by 10%, 20% and 30% using 60% of solar and 40% of wind power.
- Unit costs of the hydro generator have a right-skewed distribution
- Higher capacity in the 2° slot for both wind and solar generators.



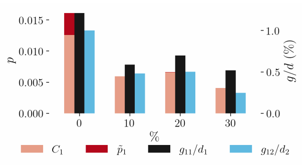


- △ denotes the mean. + markers indicate max/min values.
- Left bars: 1° slot, Right bars: 2° slot.

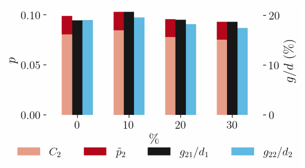
- Wind - solar integration: Aggregate capacity was increased by 10%, 20% and 30% by introducing a wind and a solar generator.
- Hydro power expansion: Aggregate capacity was increased by 10%, 20% and 30% by introducing 2 additional generators (for comparison)

	RegretNet		
Capacity Expansion	*cost*	*rgt*	*ccp*
0%	0.9470	<0.001	<0.001
Wind - solar intergration			
10%	0.7771	<0.001	<0.001
20%	0.6257	<0.001	<0.001
30%	0.5178	<0.001	<0.001
Hydro power expansion			
10%	0.7855	<0.001	<0.001
20%	0.6480	<0.001	<0.001
30%	0.5458	<0.001	<0.001

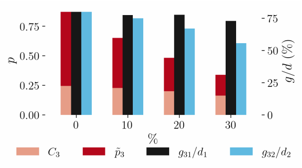
Liq-fuel Thermal



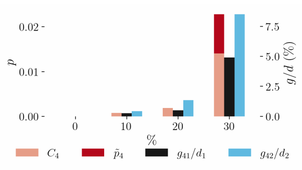
Gas/Coal Thermal



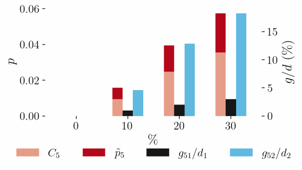
Hydro



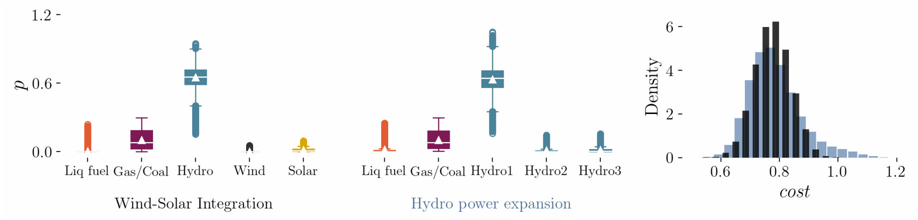
Wind



Solar



10%


1.2
0.6
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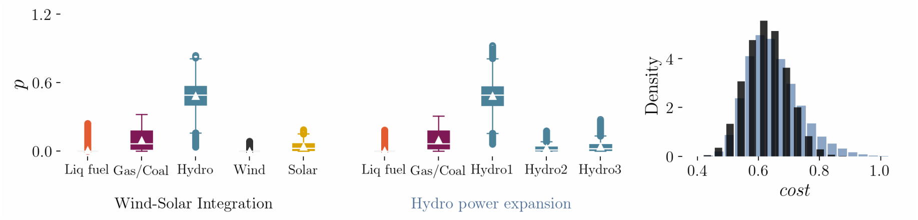
p
Liq fuel
Gas/Coal
Hydro
Wind
Solar
Liq fuel
Gas/Coal
Hydro1
Hydro2
Hydro3
Wind-Solar Integration
Hydro power expansion
6
4
2
0
Density
0.6
0.8
1.0
1.2
cost

20%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Liq fuel
Gas/Coal
Hydro1
Hydro2
Hydro3
Wind-Solar Integration
Hydro power expansion
4
2
0
Density
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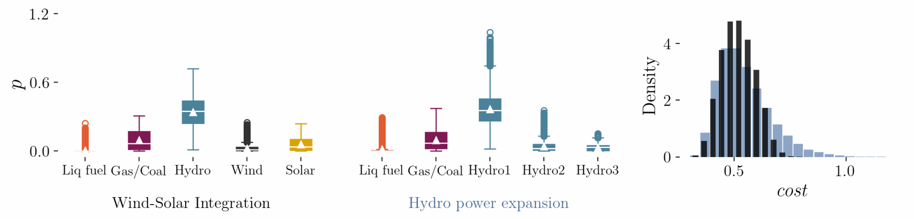
0.6
0.8
1.0
cost

30%


1.2
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Liq fuel
Gas/Coal
Hydro
Wind
Solar
Liq fuel
Gas/Coal
Hydro1
Hydro2
Hydro3
Wind-Solar Integration
Hydro power expansion
Density
4
2
0
0.5
1.0
cost

Future work

- Contamination and/or fairness constraints
- Multi-part and block bidding
- Reserve and battery storage management
- Demand response programs

References I

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