A Context-Integrated Transformer-Based Neural Network for Auction Design

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Optimal Auction Design

- One of the central topics in auction design

- Goal: design a revenue-optimal auction that satisfies:
  - Dominant Strategy Incentive Compatible (**DSIC**) :
    Truthful bidding is the dominant strategy.
  - Individually Rational (**IR**):
    Truthful bidding will receive non-negative utility.

- However, optimal auction design is hard.
  - No analytical solution for even 2-item auctions.

Optimal Auction Design through Deep Learning

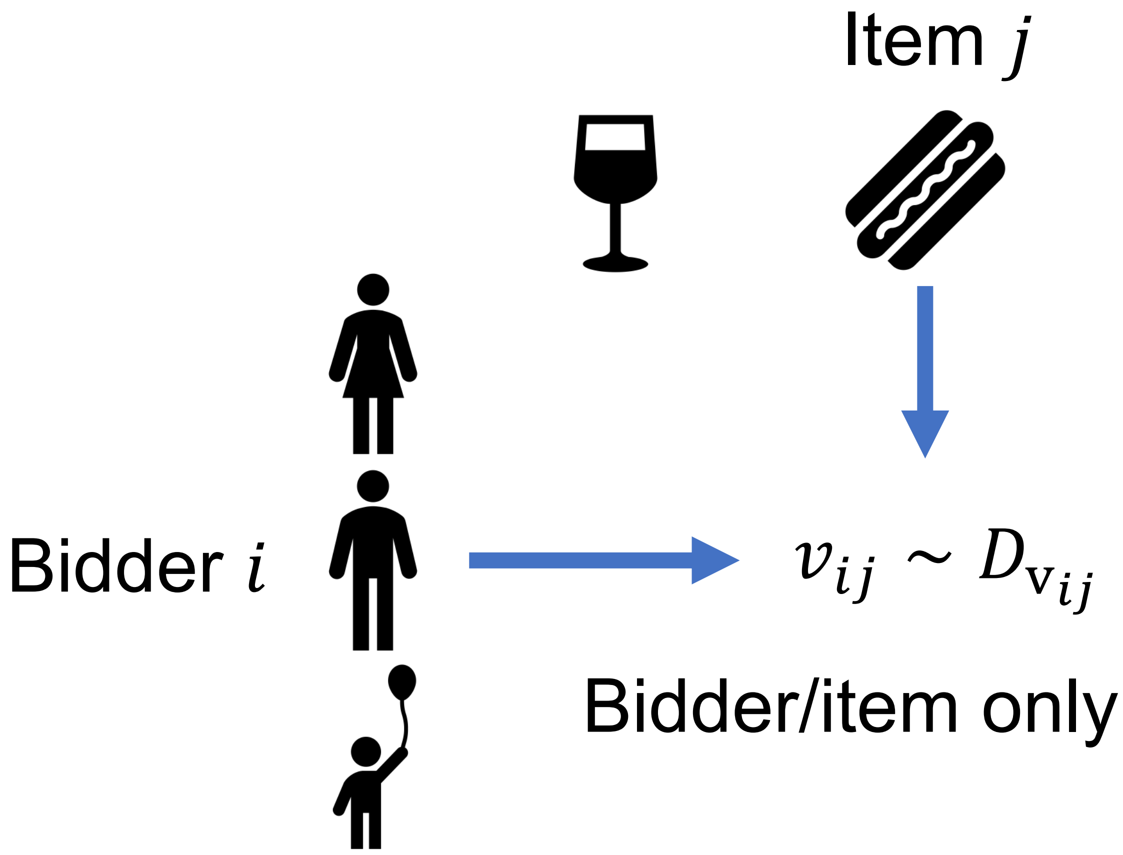
- Pioneered by RegretNet[1]
- Parameterize the auction mechanism with neural networks.
- Formulate auction design as a constrained optimization problem.
  - Objective: Maximize expected revenue
  - Constraint: DSIC
  - IR can be satisfied by mechanism construction.
- Find near-optimal solutions using gradient descent.
  - Loss = - **Revenue** + **DSIC Violation Penalty**

[1]Dütting, Paul, et al. Optimal auctions through deep learning. ICML 2019

Our Main Contributions

- We extend the deep learning approach for auction design to **contextual auction**.
- We propose **CITransNet**: a **C**ontext-**I**ntegrated **Trans**former-based neural **Net**work architecture, as the parameterized mechanism.
- Experiments show the effectiveness of CITransNet in both single-item and multi-item contextual auctions.

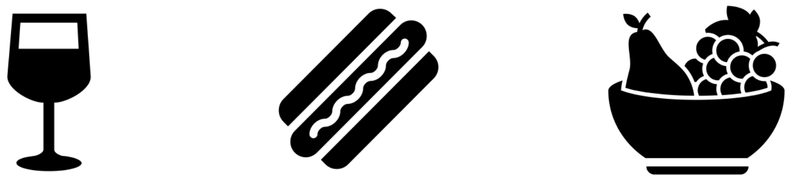
Traditional Bayesian Auction



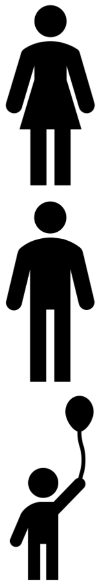
Bidder/item only identified by ID

Contextual Auction

Item j **with context $\mathbf{y}_j$**



- More representative
- More practical

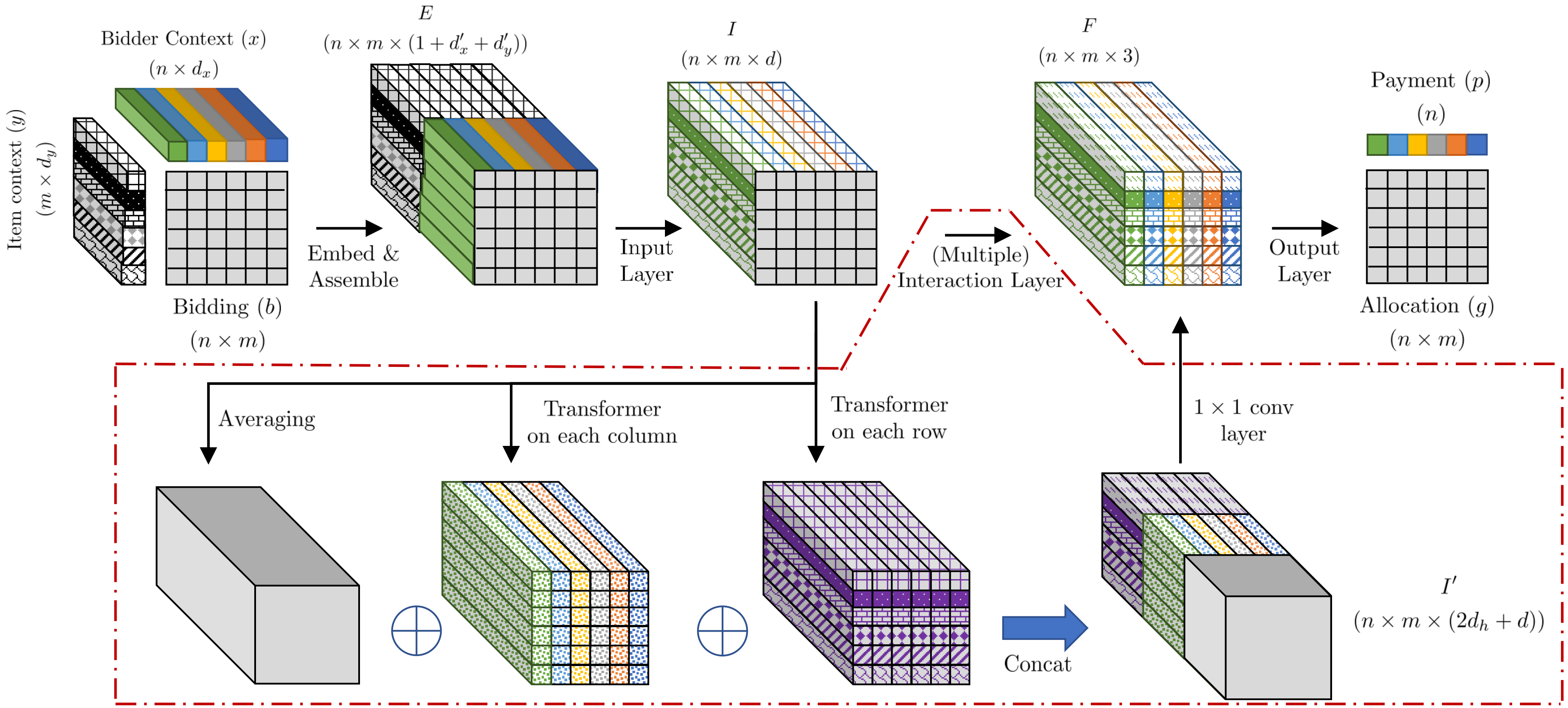


Bidder i **with context $\mathbf{x}_i$**

$$v_{ij} \sim D_{v_{\text{ij}}|x_i,y_j}$$

Bidder/item represented by **contexts** (public features)

CITransNet



Input Layer + Multiple Interaction Layers + Output Layer

Properties of CITransNet

- Context-integrated: it makes use of bids and all the contexts

- Individually Rational (IR)

- Permutation equivariant:
  permutation on inputs cause the same permutation on outputs

- The architecture is not affected by input size.

Experiment Results

- Recover Myerson results in single-item auctions.

Method	A: 3×1 $\lvert\mathcal{X}\rvert = 5, \lvert\mathcal{Y}\rvert = 1$		B: 3×1 $\lvert\mathcal{X}\rvert = 5, \lvert\mathcal{Y}\rvert = 2$		C: 5×1 $\mathcal{X}, \mathcal{Y} \subset \mathbb{R}^{10}$	
	rev	rgt	rev	rgt	rev	rgt
`Optimal`	0.594	-	0.456	-	0.367	-
`RegretNet`	0.516	<0.001	0.412	<0.001	0.329	<0.001
`EquivariantNet`	0.498	<0.001	0.403	<0.001	0.311	<0.001
`CIRegretNet`	0.594	<0.001	0.453	<0.001	0.364	<0.001
`CIEquivariantNet`	0.590	<0.001	0.452	<0.001	0.360	<0.001
`CITransNet`	0.593	<0.001	0.454	<0.001	0.366	<0.001

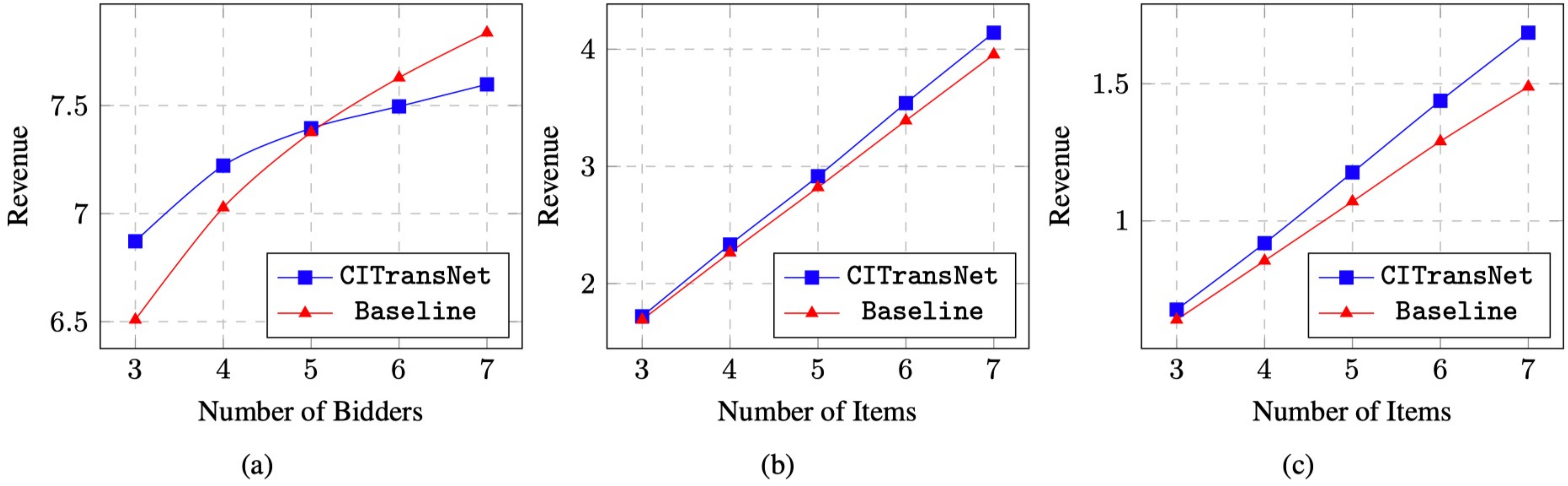
Experiment Results

- Outperform strong baselines in multi-item auctions

Method	D: 2×5 $\lvert\mathcal{X}\rvert = \lvert\mathcal{Y}\rvert = 10$		E: 3×10 $\lvert\mathcal{X}\rvert = \lvert\mathcal{Y}\rvert = 10$		F: 5×10 $\lvert\mathcal{X}\rvert = \lvert\mathcal{Y}\rvert = 10$		G: 2×5 $\mathcal{X}, \mathcal{Y} \subset \mathbb{R}^{10}$		H: 3×10 $\mathcal{X}, \mathcal{Y} \subset \mathbb{R}^{10}$		I: 5×10 $\mathcal{X}, \mathcal{Y} \subset \mathbb{R}^{10}$	
	rev	rgt	rev	rgt	rev	rgt	rev	rgt	rev	rgt	rev	rgt
`Item-wise Myerson`	2.821	-	6.509	-	7.376	-	1.071	-	2.793	-	3.684	-
`CIRegretNet`	2.803	<0.001	5.846	<0.001	6.339	<0.003	1.104	<0.001	2.424	<0.001	2.999	<0.001
`CIEquivariantNet`	2.841	<0.001	6.703	<0.001	7.602	<0.003	1.147	<0.001	2.872	<0.001	3.806	<0.001
`CITransNet`	**2.916**	<0.001	**6.872**	<0.001	**7.778**	<0.003	**1.177**	<0.001	**2.918**	<0.001	**3.899**	<0.001

Experiment Results

- Generalize well to settings with a different number of bidders or items than those in training.



Thanks for your listening!