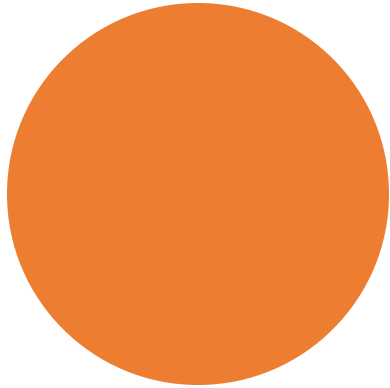


Automated Mechanism Design via Neural Networks

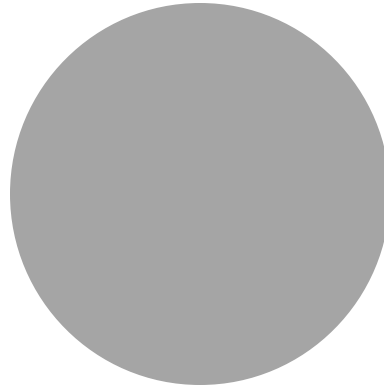
Weiran Shen, Pingzhong Tang , Song Zuo

Presented By Shaily Mishra

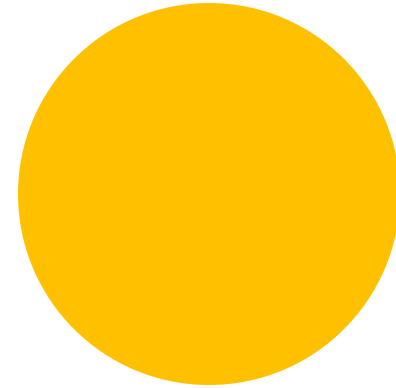
Problem Addressed



REPRESENTATION



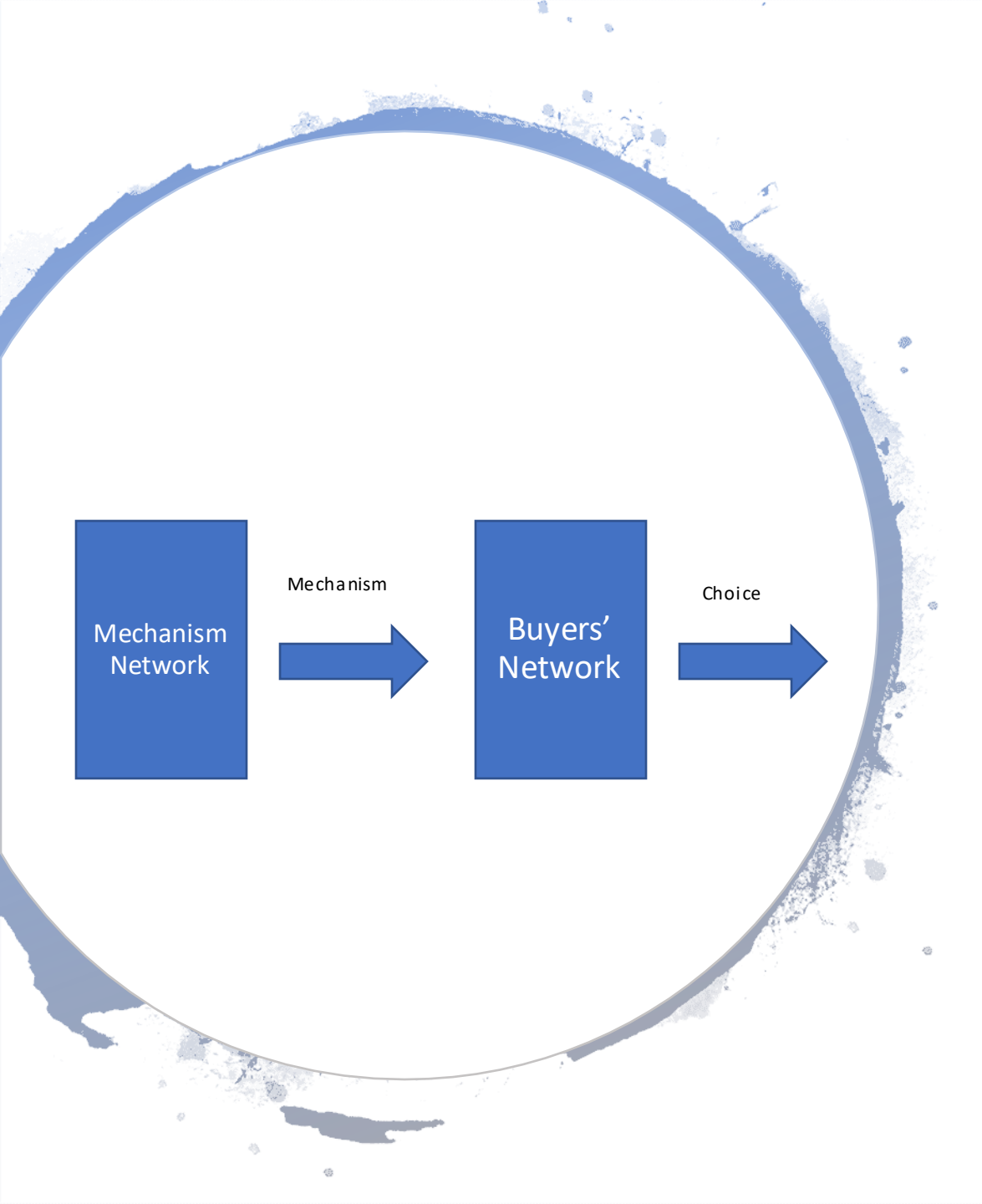
EXACTNESS



DOMAIN DEPENDENCE

Goal

- Multi item, single buyer
- Regardless of game theoretic assumptions
- Without any assumptions on valuations
- Exact IC , IR
- Almost optimal
- Any objective

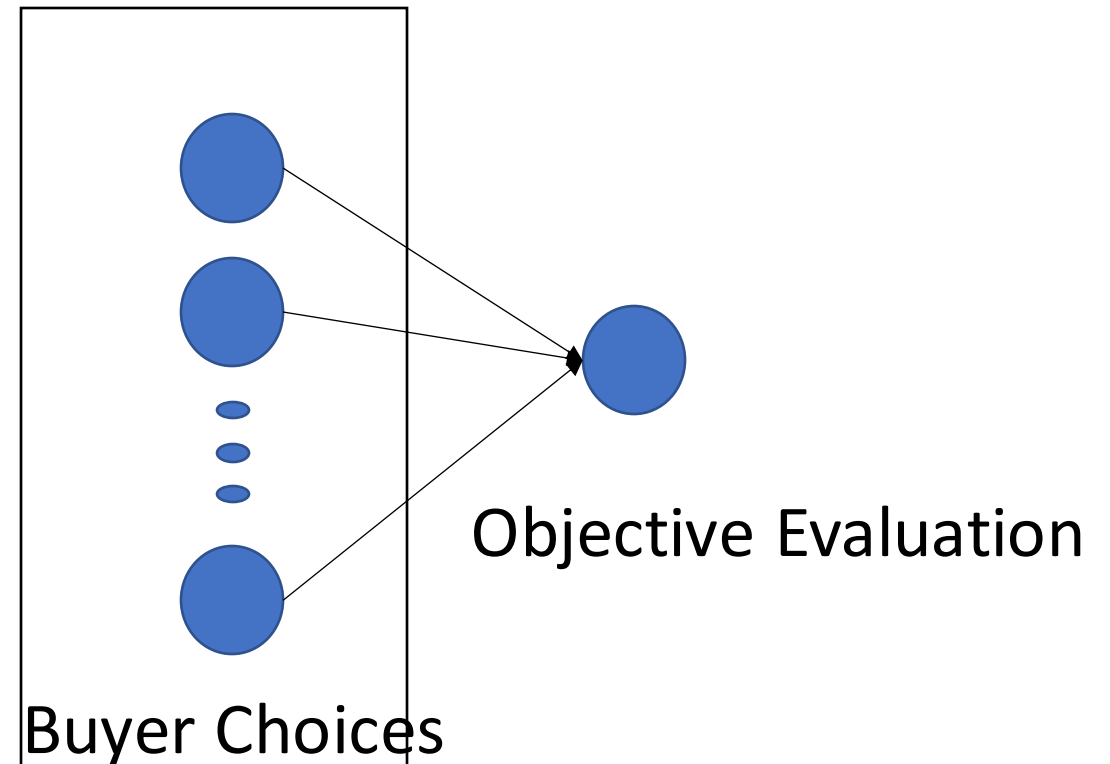


Solution

- Mechanism as menu
- Example of two item menu
 - $\{(0,0),0\}$
 - $\{(0,1),2\}$
 - $\{(1,0),3\}$
 - $\{(1,1),5\}$
- Exact IR - always has a choice of exit

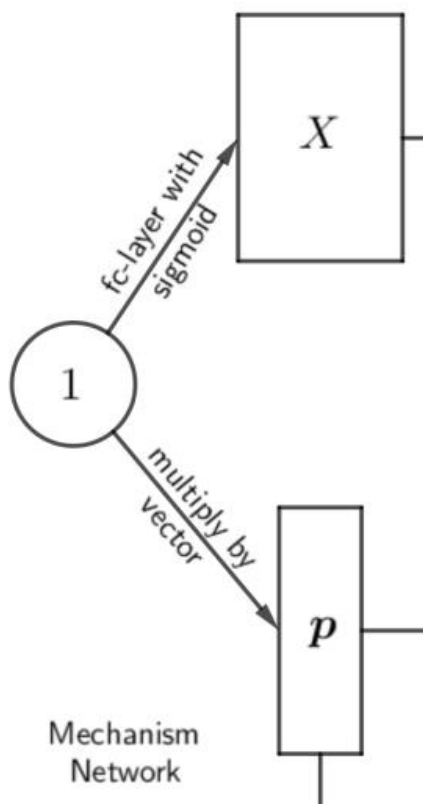
Solution – Buyers Network

- Maps mechanism to strategy
- Encoding of buyer's utility function at different valuations function
- Each node, corresponds to different valuation function, and outputs the menu item that gives maximum utility
- Expected objective is calculated using probabilities of these valuations function, and their choice result
- Generate by assumption or learn from previous data
- Exact IC



Experimental Setup – Mechanism Network

- Allocation matrix X ($m \times k$)
- $M = \text{\#items}$, $k = \text{menu size}$
- Payment vector \mathbf{p} ($k \times 1$)
- Row i of X , gives allocation of item i
- Column of X represents menu item



For $m = 3$, $k = 5$

```
-----Allocation Matrix-----  
tensor([[0., 1., 1., 1., 0.],  
        [1., 1., 1., 0., 0.],  
        [0., 1., 0., 1., 0.]])  
-----Price-----  
tensor([0.8172, 0.1233, 0.6187, 0.4816, 0.0000],
```

Experimental Setup –Buyer Network

- Assuming : additive valuation function and independent values

for $m = 3$ and $k = 5$

Valuations for all 3 items are $\sim U(0,1)$

For each item , discretize the interval to d_i discrete values

Let $d_1 = 2$, $d_2 = 3$, $d_3 = 4$

discrete values for item 1 = $\{0.5, 1\}$

discrete values for item 2 = $\{0.25, 0.5, 1\}$

discrete values for item 3 = $\{0.125, 0.25, 0.5, 1\}$

Creating m m -dimensional tensors V_1, \dots, V_m , each of size $d_1 \times d_2 \times \dots \times d_m$

i.e. Creating 3 3-dimensional tensors V_1, V_2, V_3 , each of size $2 \times 3 \times 4$

V1

```
tensor([[[[0.5000, 0.5000, 0.5000, 0.5000],  
          [0.5000, 0.5000, 0.5000, 0.5000],  
          [0.5000, 0.5000, 0.5000, 0.5000]],  
  
        [[1.0000, 1.0000, 1.0000, 1.0000],  
         [1.0000, 1.0000, 1.0000, 1.0000],  
         [1.0000, 1.0000, 1.0000, 1.0000]]]])
```

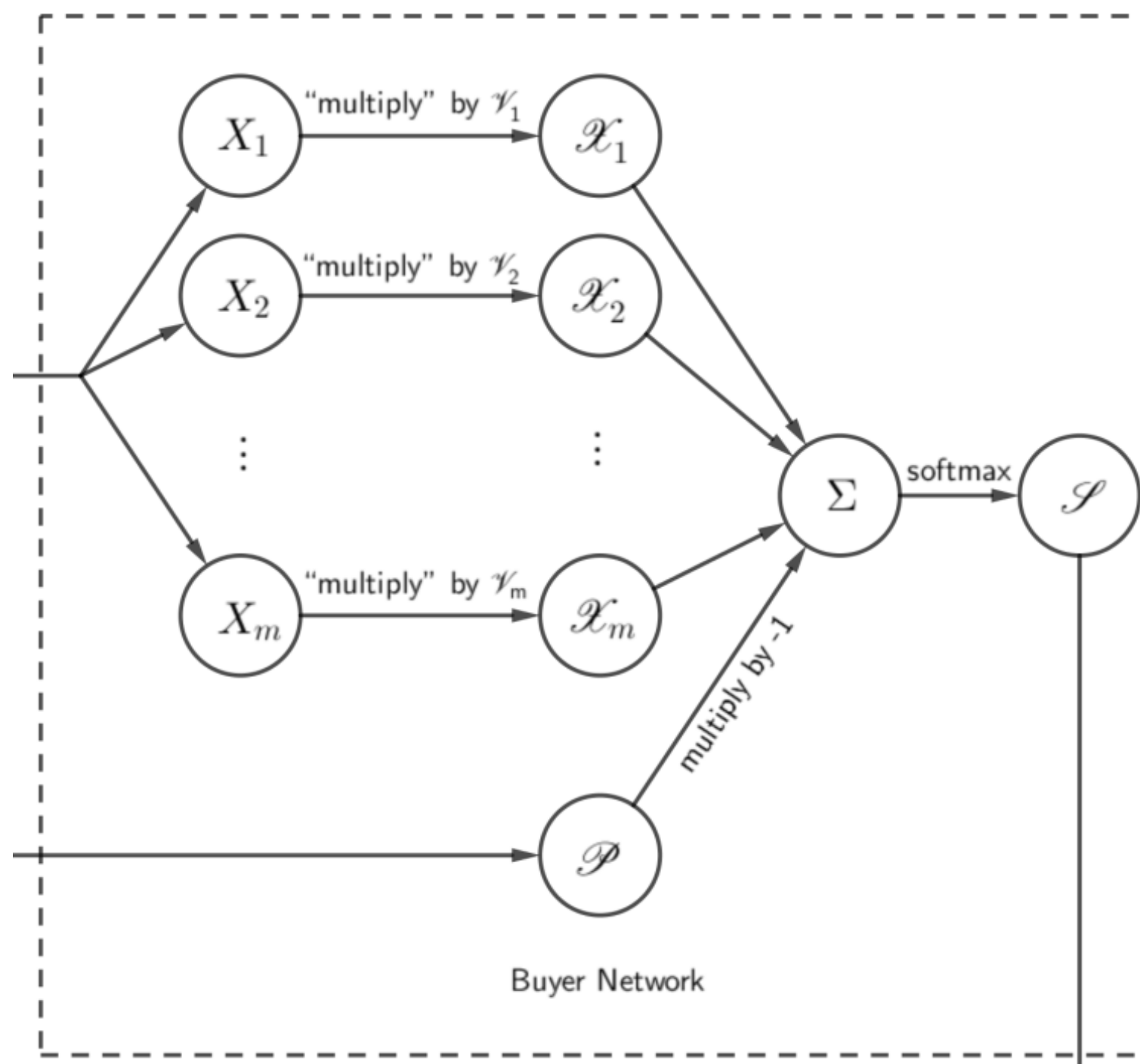
V2

```
tensor([[[[0.2500, 0.2500, 0.2500, 0.2500],  
          [0.5000, 0.5000, 0.5000, 0.5000],  
          [1.0000, 1.0000, 1.0000, 1.0000]],  
  
        [[0.2500, 0.2500, 0.2500, 0.2500],  
         [0.5000, 0.5000, 0.5000, 0.5000],  
         [1.0000, 1.0000, 1.0000, 1.0000]]]])
```

V3

```
tensor([[[[0.1250, 0.2500, 0.5000, 1.0000],  
          [0.1250, 0.2500, 0.5000, 1.0000],  
          [0.1250, 0.2500, 0.5000, 1.0000]],  
  
        [[0.1250, 0.2500, 0.5000, 1.0000],  
         [0.1250, 0.2500, 0.5000, 1.0000],  
         [0.1250, 0.2500, 0.5000, 1.0000]]]])
```


Buyer's Network



Allocation x valuation

Multiply each $X_i(k \times 1)$ with $V_i(d_1 \times d_2 \times \dots \times d_m) \Rightarrow Y_i (d_1 \times d_2 \times \dots \times d_m \times k)$

i.e. $Y_i (2 \times 3 \times 4 \times 5)$, gives us the value of allocated item i for different valuation

Y1

```
tensor([[[[0.0000, 0.5000, 0.5000, 0.5000, 0.0000],
           [0.0000, 0.5000, 0.5000, 0.5000, 0.0000],
           [0.0000, 0.5000, 0.5000, 0.5000, 0.0000],
           [0.0000, 0.5000, 0.5000, 0.5000, 0.0000]],

        [[0.0000, 0.5000, 0.5000, 0.5000, 0.0000],
          [0.0000, 0.5000, 0.5000, 0.5000, 0.0000],
          [0.0000, 0.5000, 0.5000, 0.5000, 0.0000],
          [0.0000, 0.5000, 0.5000, 0.5000, 0.0000]],

        [[0.0000, 0.5000, 0.5000, 0.5000, 0.0000],
          [0.0000, 0.5000, 0.5000, 0.5000, 0.0000],
          [0.0000, 0.5000, 0.5000, 0.5000, 0.0000],
          [0.0000, 0.5000, 0.5000, 0.5000, 0.0000]]],

       [[0.0000, 1.0000, 1.0000, 1.0000, 0.0000],
        [0.0000, 1.0000, 1.0000, 1.0000, 0.0000],
        [0.0000, 1.0000, 1.0000, 1.0000, 0.0000],
        [0.0000, 1.0000, 1.0000, 1.0000, 0.0000]],

       [[0.0000, 1.0000, 1.0000, 1.0000, 0.0000],
        [0.0000, 1.0000, 1.0000, 1.0000, 0.0000],
        [0.0000, 1.0000, 1.0000, 1.0000, 0.0000],
        [0.0000, 1.0000, 1.0000, 1.0000, 0.0000]],

       [[0.0000, 1.0000, 1.0000, 1.0000, 0.0000],
        [0.0000, 1.0000, 1.0000, 1.0000, 0.0000],
        [0.0000, 1.0000, 1.0000, 1.0000, 0.0000],
        [0.0000, 1.0000, 1.0000, 1.0000, 0.0000]]]])
```

Y2

```
tensor([[[[0.2500, 0.2500, 0.2500, 0.0000, 0.0000],
           [0.2500, 0.2500, 0.2500, 0.0000, 0.0000],
           [0.2500, 0.2500, 0.2500, 0.0000, 0.0000],
           [0.2500, 0.2500, 0.2500, 0.0000, 0.0000]],

        [[0.5000, 0.5000, 0.5000, 0.0000, 0.0000],
          [0.5000, 0.5000, 0.5000, 0.0000, 0.0000],
          [0.5000, 0.5000, 0.5000, 0.0000, 0.0000],
          [0.5000, 0.5000, 0.5000, 0.0000, 0.0000]],

        [[1.0000, 1.0000, 1.0000, 0.0000, 0.0000],
          [1.0000, 1.0000, 1.0000, 0.0000, 0.0000],
          [1.0000, 1.0000, 1.0000, 0.0000, 0.0000],
          [1.0000, 1.0000, 1.0000, 0.0000, 0.0000]]],

       [[0.2500, 0.2500, 0.2500, 0.0000, 0.0000],
        [0.2500, 0.2500, 0.2500, 0.0000, 0.0000],
        [0.2500, 0.2500, 0.2500, 0.0000, 0.0000],
        [0.2500, 0.2500, 0.2500, 0.0000, 0.0000]],

       [[0.5000, 0.5000, 0.5000, 0.0000, 0.0000],
        [0.5000, 0.5000, 0.5000, 0.0000, 0.0000],
        [0.5000, 0.5000, 0.5000, 0.0000, 0.0000],
        [0.5000, 0.5000, 0.5000, 0.0000, 0.0000]],

       [[1.0000, 1.0000, 1.0000, 0.0000, 0.0000],
        [1.0000, 1.0000, 1.0000, 0.0000, 0.0000],
        [1.0000, 1.0000, 1.0000, 0.0000, 0.0000],
        [1.0000, 1.0000, 1.0000, 0.0000, 0.0000]]]])
```

Y3

```
tensor([[[[0.0000, 0.1250, 0.0000, 0.1250, 0.0000],
           [0.0000, 0.2500, 0.0000, 0.2500, 0.0000],
           [0.0000, 0.5000, 0.0000, 0.5000, 0.0000],
           [0.0000, 1.0000, 0.0000, 1.0000, 0.0000]],

        [[0.0000, 0.1250, 0.0000, 0.1250, 0.0000],
          [0.0000, 0.2500, 0.0000, 0.2500, 0.0000],
          [0.0000, 0.5000, 0.0000, 0.5000, 0.0000],
          [0.0000, 1.0000, 0.0000, 1.0000, 0.0000]],

        [[0.0000, 0.1250, 0.0000, 0.1250, 0.0000],
          [0.0000, 0.2500, 0.0000, 0.2500, 0.0000],
          [0.0000, 0.5000, 0.0000, 0.5000, 0.0000],
          [0.0000, 1.0000, 0.0000, 1.0000, 0.0000]]],

       [[0.0000, 0.1250, 0.0000, 0.1250, 0.0000],
        [0.0000, 0.2500, 0.0000, 0.2500, 0.0000],
        [0.0000, 0.5000, 0.0000, 0.5000, 0.0000],
        [0.0000, 1.0000, 0.0000, 1.0000, 0.0000]],

       [[0.0000, 0.1250, 0.0000, 0.1250, 0.0000],
        [0.0000, 0.2500, 0.0000, 0.2500, 0.0000],
        [0.0000, 0.5000, 0.0000, 0.5000, 0.0000],
        [0.0000, 1.0000, 0.0000, 1.0000, 0.0000]],

       [[0.0000, 0.1250, 0.0000, 0.1250, 0.0000],
        [0.0000, 0.2500, 0.0000, 0.2500, 0.0000],
        [0.0000, 0.5000, 0.0000, 0.5000, 0.0000],
        [0.0000, 1.0000, 0.0000, 1.0000, 0.0000]]]])
```

```

- Summation
tensor([[[[0.2500, 0.8750, 0.7500, 0.6250, 0.0000],
          [0.2500, 1.0000, 0.7500, 0.7500, 0.0000],
          [0.2500, 1.2500, 0.7500, 1.0000, 0.0000],
          [0.2500, 1.7500, 0.7500, 1.5000, 0.0000]],

        [[0.5000, 1.1250, 1.0000, 0.6250, 0.0000],
          [0.5000, 1.2500, 1.0000, 0.7500, 0.0000],
          [0.5000, 1.5000, 1.0000, 1.0000, 0.0000],
          [0.5000, 2.0000, 1.0000, 1.5000, 0.0000]],

        [[1.0000, 1.6250, 1.5000, 0.6250, 0.0000],
          [1.0000, 1.7500, 1.5000, 0.7500, 0.0000],
          [1.0000, 2.0000, 1.5000, 1.0000, 0.0000],
          [1.0000, 2.5000, 1.5000, 1.5000, 0.0000]]]],

       [[[0.2500, 1.3750, 1.2500, 1.1250, 0.0000],
          [0.2500, 1.5000, 1.2500, 1.2500, 0.0000],
          [0.2500, 1.7500, 1.2500, 1.5000, 0.0000],
          [0.2500, 2.2500, 1.2500, 2.0000, 0.0000]],

        [[0.5000, 1.6250, 1.5000, 1.1250, 0.0000],
          [0.5000, 1.7500, 1.5000, 1.2500, 0.0000],
          [0.5000, 2.0000, 1.5000, 1.5000, 0.0000],
          [0.5000, 2.5000, 1.5000, 2.0000, 0.0000]],

        [[1.0000, 2.1250, 2.0000, 1.1250, 0.0000],
          [1.0000, 2.2500, 2.0000, 1.2500, 0.0000],
          [1.0000, 2.5000, 2.0000, 1.5000, 0.0000],
          [1.0000, 3.0000, 2.0000, 2.0000, 0.0000]]]])

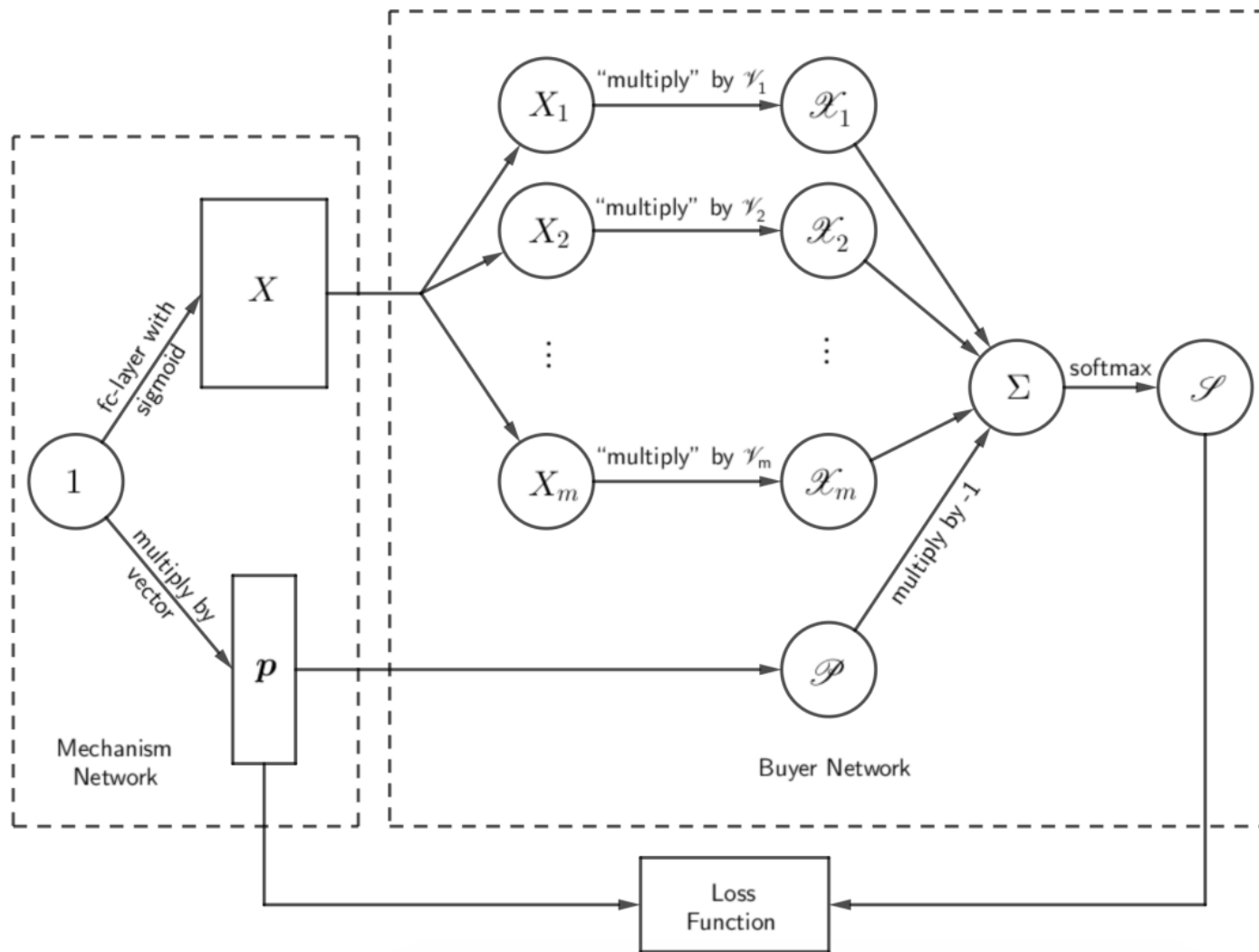
```

- Each entry (i,j,k,l) :
 - i -> valuation of item 1
 - j -> valuation of item 2
 - k -> valuation of item 3
 - l -> menu item
- Entry for (0,0,0,0) corresponds to (0.5,0.25,0.125) item valuation and allocation (0,1,0) hence the value obtained is 0.25.
- Similarly entry (0,0,0,1) corresponds to (0.5,0.25,0.125) item valuation and allocation (1,1,1), hence the value obtained is 0.875.

Taking softmax of utility across menu item

```
tensor([[[[0.1933, 0.3003, 0.2214, 0.1344, 0.1506],  
          [0.1828, 0.3216, 0.2092, 0.1440, 0.1424],  
          [0.1614, 0.3648, 0.1848, 0.1633, 0.1257],  
          [0.1202, 0.4479, 0.1377, 0.2005, 0.0937]],  
  
        [[0.2063, 0.3205, 0.2363, 0.1117, 0.1252],  
          [0.1951, 0.3434, 0.2234, 0.1197, 0.1184],  
          [0.1724, 0.3897, 0.1974, 0.1358, 0.1046],  
          [0.1286, 0.4791, 0.1472, 0.1670, 0.0780]],  
  
        [[0.2276, 0.3534, 0.2605, 0.0747, 0.0837],  
          [0.2153, 0.3789, 0.2465, 0.0801, 0.0792],  
          [0.1905, 0.4304, 0.2181, 0.0910, 0.0701],  
          [0.1423, 0.5302, 0.1629, 0.1121, 0.0524]]],  
  
       [[0.1356, 0.3473, 0.2560, 0.1555, 0.1057],  
        [0.1271, 0.3688, 0.2399, 0.1651, 0.0990],  
        [0.1104, 0.4112, 0.2083, 0.1841, 0.0860],  
        [0.0796, 0.4891, 0.1503, 0.2189, 0.0620]],  
  
       [[0.1439, 0.3686, 0.2717, 0.1285, 0.0873],  
        [0.1350, 0.3917, 0.2548, 0.1366, 0.0819],  
        [0.1174, 0.4373, 0.2216, 0.1525, 0.0712],  
        [0.0849, 0.5215, 0.1603, 0.1818, 0.0515]],  
  
       [[0.1573, 0.4028, 0.2969, 0.0852, 0.0579],  
        [0.1477, 0.4286, 0.2788, 0.0906, 0.0544],  
        [0.1287, 0.4796, 0.2430, 0.1014, 0.0474],  
        [0.0935, 0.5742, 0.1765, 0.1214, 0.0344]]]])
```

- Calculate the utility, and then take softmax
- For each value profile, choose the strategy that gives highest weight



- Objective : Maximize revenue

$$\text{Loss} = -\text{REV} = -\sum_{v \in V} \Pr[v] \mathbf{p}^T \mathbf{s}(v),$$

Unified Network



Evaluation

Uniform $[0, c] \times [0, 1]$

Correlated Distribution: Uniform Triangle (Proves theoretical result)

Restricted Menu Size (Proves theoretical result)

Unit-Demand Buyer

Combinatorial Value

Deterministic Mechanisms