#### More Linear Programming Examples II

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Read Chapter 1.1, 1.2, 2.1, 2.2, Appendices A, B&D in Textbook

## LP Example 8: Data Classification - Business or Personal?

Build a model that will predict a probability for each credit card transaction indicating whether the transaction is business or personal related.

- There is no training data where particular transactions are identified as being personal, we used personal remittances as the best proxy
- On the transaction side, we focused on the industry code of each transaction as a key initial differentiator between transactions
- Developed a LP model to establish probabilities for each industry code that indicate the likelihood that dollars spent in that code will be personal spending.

### Transaction Types by Industrial Codes



### Business Analytics

For each of the industry codes, the model will determine a probability which indicates the likelihood that a transaction was personal.



### Model Example

*For each of the industry codes, the model will determine a probability (in red) which indicates the likelihood that a transaction was personal. The goal is to minimize the sum of the squares of the differences (in blue).*



### LP Model: Constrained Linear Regression

*Our model will determine the probability that a transaction from each industry code is personal in such a manner which will minimize the sum of the squared errors (between predicted personal remittances and actual personal remittances).*

Min  
\n
$$
\sum_{i} |\sum_{j} a_{ij} x_{j} - b_{i}|
$$
\n
$$
\text{s.t.} \quad 0 \le x_{j} \le 1, \forall j.
$$

- Let *x<sup>j</sup>* be such a probability that a transaction is personal for industry code *j*
- $a_{i,j}$  transaction amount for account *i* and industry code *j*
- *bi*  amount paid by personal remit for account *i*
- $\sum_{i} a_{i,i} x_{i}$  the expected personal expenses for account *i*
- We'd like to choose *x<sup>j</sup>* such that *∑jai,j x<sup>j</sup>* matches *b<sup>i</sup>* for ALL *i*

#### How to Linearize the Abs Function I

To dealing the abs function, we introduce auxiliary variables *y<sup>i</sup>*

$$
|z_i|=y_i, i=1,\ldots,m.
$$

Relax it to linear inequalities

$$
-y_i \le z_i \le y_i, i = 1, \ldots, m.
$$

If the sum of  $y_i$ s is minimized, the equality must hold



#### How to Linearize the Abs Function II

Introduce auxiliary variables *y'<sup>i</sup>* and *y"<sup>i</sup>*

$$
z_i = y'_i - y''_i, y'_i \ge 0, y''_i \ge 0, i = 1, ..., m.
$$

Relax it to linear inequalities

$$
\min |z_i| \Leftrightarrow \min y'_{i} + y''_{i}
$$

If the sum of  $y_i$ s is minimized, the equality must hold



# LP Example 9: Reinforcement Learning and Markov Decision Process

- Markov decision process provides a mathematical framework for modeling sequential decision-making in situations where outcomes are partly random and partly under the control of a decision maker, and it is called Reinforcement Learning lately.
- MDPs are useful for studying a wide range of optimization problems solved via dynamic programming, where it was known at least as early as the 1950s (cf. Shapley 1953, Bellman 1957).
- Modern applications include dynamic planning, social networking, and almost all other dynamic/sequential-decisionmaking problems in Mathematical, Physical, Management, Economics, and Social Sciences.
- MDP is characterized by States and Actions; and at each time step, the process is in a state and the decision maker chooses an action to optimize a long-term goal.



Each state *i* (in Square) is equipped with a set of actions  $A_i$  , and they are colored **in red (status quo move), blue (shortcut move); and each of them incurs an immediate cost** *c<sup>j</sup>* **. In this example, all actions have zero cost except the one from the state 4 (trap) to the final termination state 5 (Exit state which goes back to itself ). Each action is associated with transition probability node (circle) with distribution vector P<sup>j</sup> to all states.**

# Cost-to-Go values of a Policy



**A policy is a set of actions taken in each State at anytime, and it defines an expected Cost-to-Go value for each State (the overall present cost if starting from this very state). Assuming there is no discount and the current policy takes all-red actions, the corresponding expected cost-to-go state-values would be given above, together with expected values for blue-actions.**

**Clearly, this policy is not optimal…** 

# Cost-to-Go values of another Policy



- **If the current policy is taking (red, red, red, blue, red) actions, the corresponding expected cost-to-go state-values would be given above, together with expected values for other actions. This policy is optimal.**
- **An optimal policy is a policy that for each state there is no action-switch that results in a lower cost.**

# Cost-to-Go values of the Maze Run

- $y_i$ : the expected overall present cost if stating from State i.
- State 5 is a trap
- State 6 is the exit state
- Each other state has two options: Go directly to the next state or a short-cut go to other states with uncertainties



• The cost-to-go values of the optimal policy with discount factor ϒ for this simple example should meet the following conditions

$$
y_{6} = 0+ \gamma y_{1}, \quad y_{5} = 1+ \gamma y_{6}
$$
\n
$$
y_{4} = \min\{0+ \gamma y_{5}, 0+\gamma(0.2y_{5}+0.8y_{6}),
$$
\n
$$
y_{3} = \min\{0+ \gamma y_{4}, 0+\gamma(0.5y_{5}+0.5y_{6})\}
$$
\n
$$
y_{2} = \min\{0+ \gamma y_{3}, 0+\gamma(0.33y_{4}+0.33y_{5}+0.33y_{6})\}
$$
\n
$$
y_{1} = \min\{0+ \gamma y_{2}, 0+\gamma(0.25y_{3}+0.25y_{4}+0.25y_{5}+0.25y_{6})\}
$$

max y<sub>1</sub> + y<sub>2</sub> + y<sub>3</sub> + y<sub>4</sub> + y<sub>5</sub> + y<sub>6</sub>  
\ns.t. y<sub>6</sub> 
$$
\le
$$
 0+  $\gamma$ y<sub>1</sub>  
\ny<sub>5</sub>  $\le$  1+  $\gamma$  y<sub>6</sub>  
\ny<sub>4</sub>  $\le$  0+  $\gamma$  y<sub>5</sub>  
\ny<sub>4</sub>  $\le$  0+  $\gamma$ (0.2y<sub>5</sub>+y<sub>6</sub>)  
\ny<sub>3</sub>  $\le$  0+  $\gamma$ y<sub>4</sub>  
\ny<sub>3</sub>  $\le$  0+  $\gamma$ y<sub>4</sub>  
\ny<sub>2</sub>  $\le$  0+  $\gamma$ y<sub>3</sub>  
\ny<sub>2</sub>  $\le$  0+  $\gamma$ (0.33y<sub>4</sub>+0.33y<sub>5</sub>+0.33y<sub>6</sub>)  
\ny<sub>1</sub>  $\le$  0+  $\gamma$ y<sub>2</sub>  
\ny<sub>1</sub>  $\le$  0+  $\gamma$ (0.25y<sub>3</sub>+0.25y<sub>4</sub>+0.25y<sub>5</sub>+0.25y<sub>6</sub>)

LP Formulation of the Maze Run

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# MDP/RL State/Action Environment



# Cost-to-Go values and the LP formulation

• In general, let *y* <sup>∈</sup> *R <sup>m</sup>* represent the expected present cost-to-go values of the *m* states, respectively, for a given policy. Then, the cost-to-go vector of the optimal policy, with the discount factor γ, by Bellman's Principle is a Fixed Point:

$$
y_i = \min\{c_j + \gamma p_j^T y, j \in A_i\}, \forall i,
$$

 $j_i = \arg \min \{ c_j + \gamma p_j^T y, j \in A_i \}, \forall i.$ *T*  $a_i = \arg \min \{ c_j + \gamma p'_j y, j \in A_i \}, \forall i$ 

Such a fixed-point computation can be formulated as an LP

max 
$$
\sum_{i} y_i
$$
  
s.t.  $y_i \le c_j + \gamma p_j^T y, \forall j \in A_i; \forall i$ .

• The maximization is trying to pushing up each yi to the highest possible so that it equal to min-argument. When the optimal y is found, one can then find the index of the original optimal action/policy using argmin.

Yinyu Ye, Mini-course Lecture Notes #3



## Action Costs of Tic-Tac-Toe Game



## LP Formulation Summary

#### Modeling Process

- Understand the problem
- Collect information and data
- Identify and define the decision variables
- formulate the objective function
- Isolate and formulate the constraints
- How to deal with piecewise linear and abs functions:
- $|x| \Rightarrow -z \le x \le z$ , then replace  $|x|$  with z in the objective

 $|x| \Rightarrow x = z' - z''$ ,  $(z', z'') \ge 0$ , then replace  $|x|$  with  $z' + z''$  in the objective

Business Analytics and Machine Learning/Decisions: Business Decisions based on Analytical Models and Solutions