



BITS Pilani

Social Media Analytics

Garima Jindal
Faculty Department



Social Media Analytics

Lecture No. 11

Recap

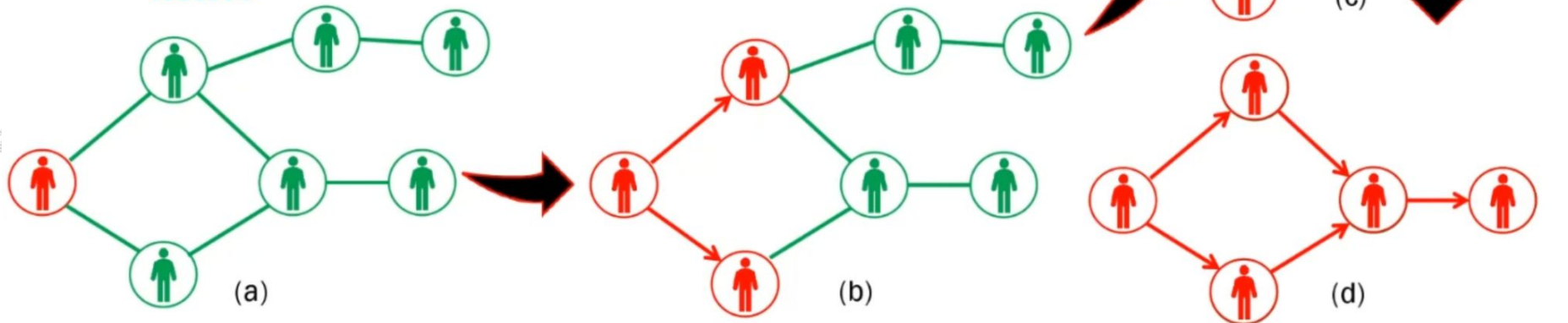


- Information discussion.
- Types of Diffusion Models
 - Decision-Based Diffusion Models
 - Probabilistic-Based Diffusion Models
- What are the advantage and disadvantage
- how they evolve over time

Work Integrated Learning Programmes

Information Diffusion: Terminologies

- ❑ A **Contagion** is an entity that spreads across a network
- ❑ **Adoption** refers to the event of infection or diffusion. Also known as activation
- ❑ **Adopters** represent the final set of infected nodes
- ❑ Final propagation tree obtained by the spread of the infection is known as **cascade**



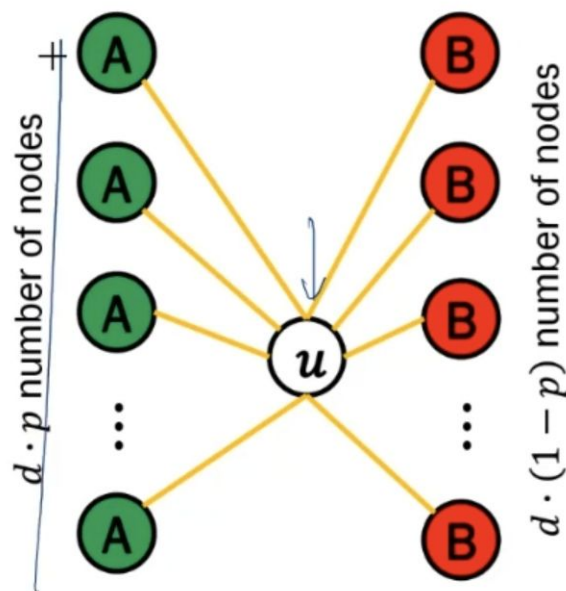
Decision-based Cascade Model: Two-player Coordination Game

u 's decision	v 's decision	Payoff
A	A	a^*
B	B	b^*
A	B	0
B	A	0

Payoff distribution for different adoption strategies
* a and b are positive constants

- ❑ A and B: **two possible strategies** that each node in network $G(V, E)$ could adopt
- ❑ Each node u will play its own **independent** game
- ❑ **Final payoff** is the sum of payoffs for all the games
- ❑ To calculate the required threshold at which a node u would decide to go with strategy A

Decision-based Cascade Model: Two-player Coordination Game



☐ Node u has d neighbours

☐ p fraction of neighbours adopt strategy A

☐ Rest adopts strategy B

☐ Total payoff for node u if it goes with strategy A = $a \cdot d \cdot p$

☐ Total payoff for node u if it goes with strategy B = $b \cdot d \cdot (1 - p)$

☐ Node u would adopt contagion A if

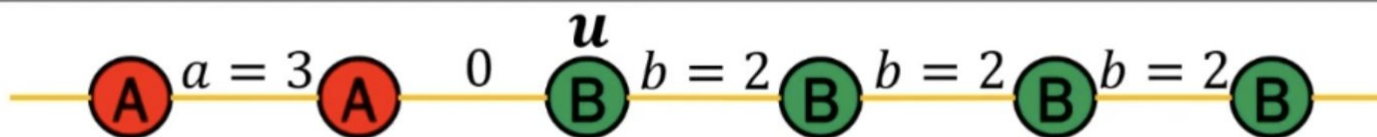
$$p \geq \frac{b}{a+b}$$

Multiple Choice Decision-based Cascade Model

- ☐ Allows a node to adopt more than one strategy/behavior
- ☐ In case a node prefers to go with both the strategies A and B, it would incur an additional cost c
- ☐ The revised payoff distribution:

u 's decision	v 's decision	Payoff
AB	A	a^*
AB	B	b^*
AB	AB	$\max(a, b)$
Payoff for a multiple choice decision model		
* a and b are positive constants		

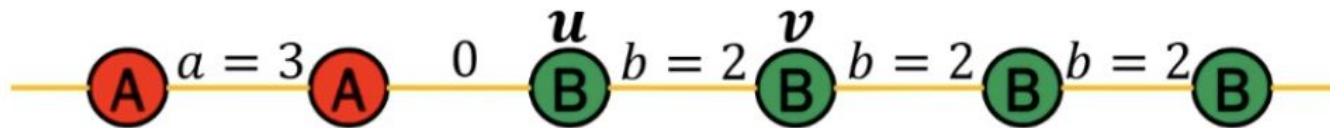
Cascades for Infinite Chain Networks: Single Choice



- ☐ Consider the case: $a = 3, b = 2$
- ☐ Two possible choice for node u
 - ☐ Stick with **strategy B**, total payoff: $0 + 2 = 2$
 - ☐ Switch to **strategy A**, total payoff: $3 + 0 = 3$
- ☐ So, node u would adopt strategy A
- ☐ And the cascade continues...



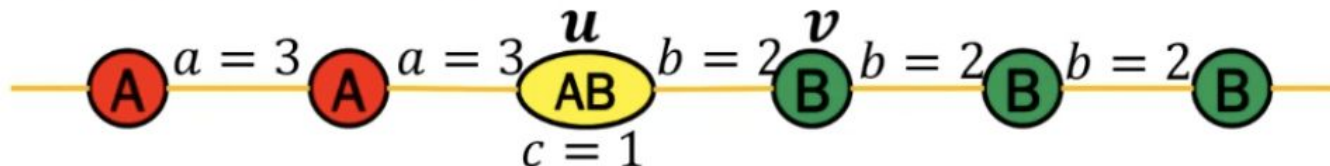
Cascades for Infinite Chain Networks: Multiple Choice: Case I



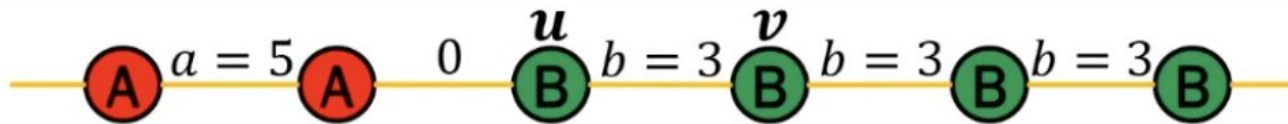
- ☐ Consider the case: $a = 3, b = 2, c = 1$
- ☐ Two possible choice for node u
 - ☐ Stick with **strategy B**, total payoff: $0 + 2 = 2$
 - ☐ Switch to **strategy A**, total payoff: $3 + 0 = 3$
 - ☐ Switch to **strategy AB**, total payoff: $3 + 2 - 1 = 4$

☐ So, node u would adopt strategy AB

☐ And system is stable now!!



Cascades for Infinite Chain Networks: Multiple Choice: Case II



Consider the case: $a = 5, b = 3, c = 1$

Two possible choices for node u

Stick with **strategy B**, total payoff: $0 + 3 = 3$

Switch to **strategy A**, total payoff: $5 + 0 = 5$

Switch to **strategy AB**, total payoff: $5 + 3 - 1 = 7$

So, node u would adopt strategy AB

Two possible choices for node v

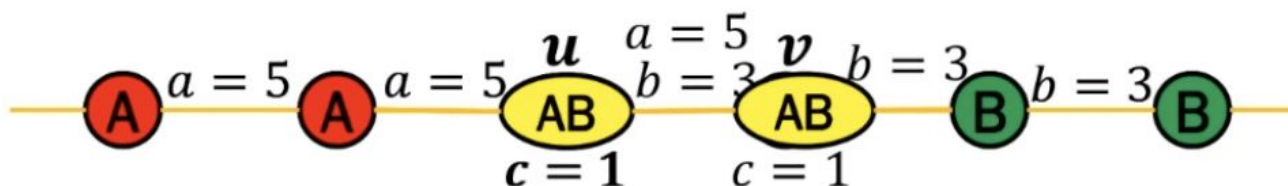
Stick with **strategy B**, total payoff: $3 + 3 = 6$

Switch to **strategy A**, total payoff: $5 + 0 = 5$

Switch to **strategy AB**, total payoff: $5 + 3 - 1 = 7$

So, node v would adopt strategy AB

And the cascade continues!!

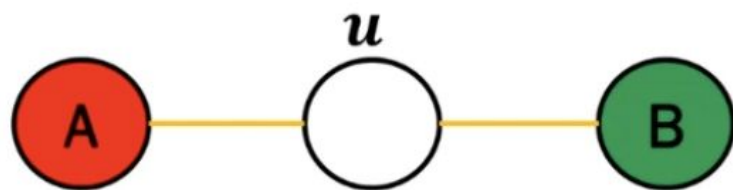


Cascade in Infinite Chain Networks: Generic Model

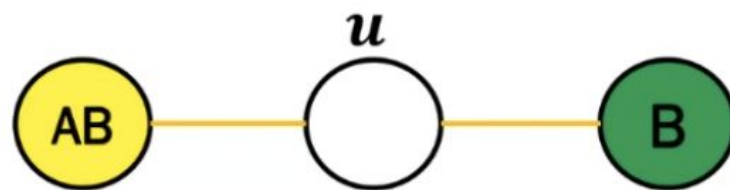
□ Let us consider an infinite chain network with strategy set $\{A, B, AB\}$

□ We consider the scenario: $a = a, b = 1, c = c$

□ Two possible cases may arise:

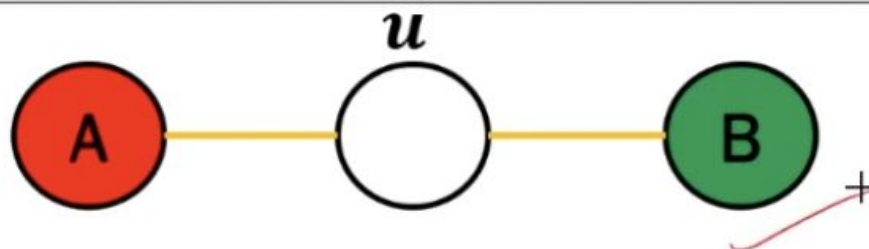


Case A



Case B

Generic Model: Case A

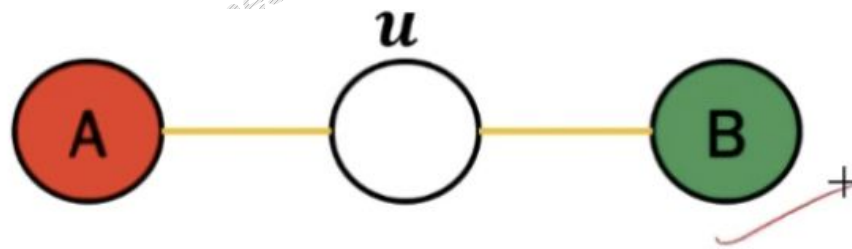


Three possible options for node u

1. Adopt Behavior A; Payoff = $a + 0 = a$
2. Adopt Behavior B; Payoff = $0 + 1 = 1$
3. Adopt Behavior AB; Payoff = $a + 1 - c$

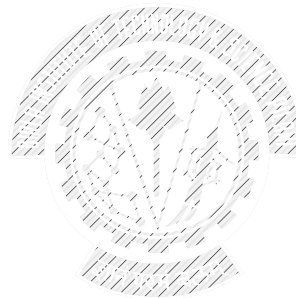
Breakpoint Equations:

- a. B versus A: $a = 1, a < 1$: Prefer strategy B; $a > 1$: Prefer strategy A
- b. AB versus B: $a = c, a < c$: Prefer strategy B; $a > c$: Prefer strategy AB
- c. A versus AB: $c = 1, c < 1$: Prefer strategy AB; $c > 1$: Prefer strategy A



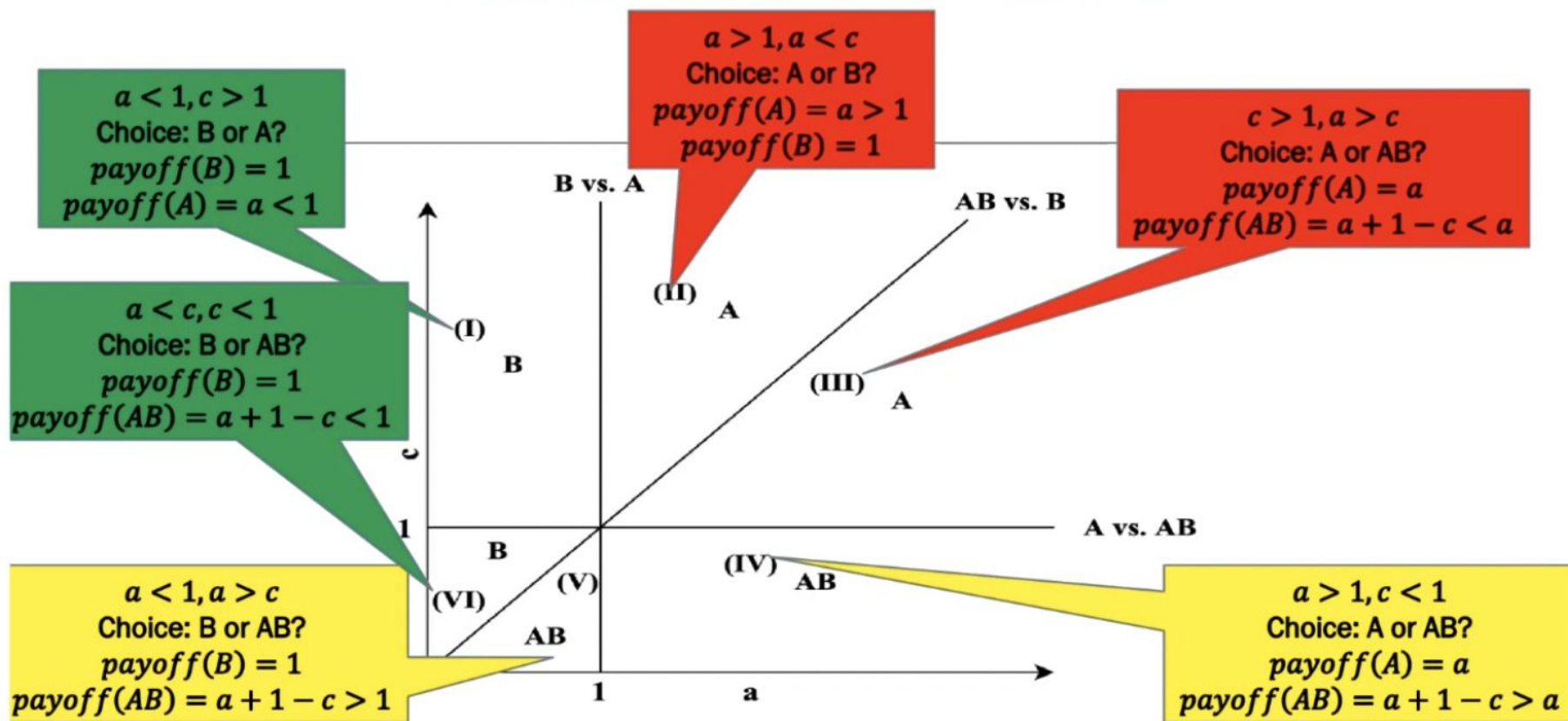
Three possible options for node u

1. Adopt Behavior A; Payoff = $a + 0 = a$
2. Adopt Behavior B; Payoff = $0 + 1 = 1$
3. Adopt Behavior AB; Payoff = $a + 1 - c$

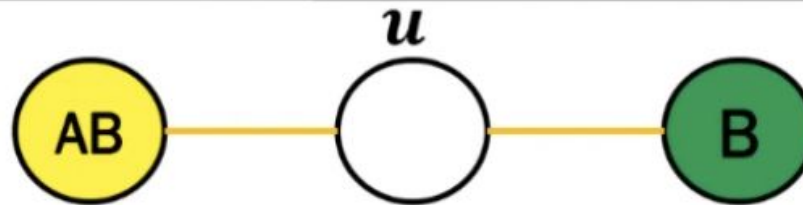


Work Integrated Learning Programmes

Generic Model: Case A



Generic Model: Case B



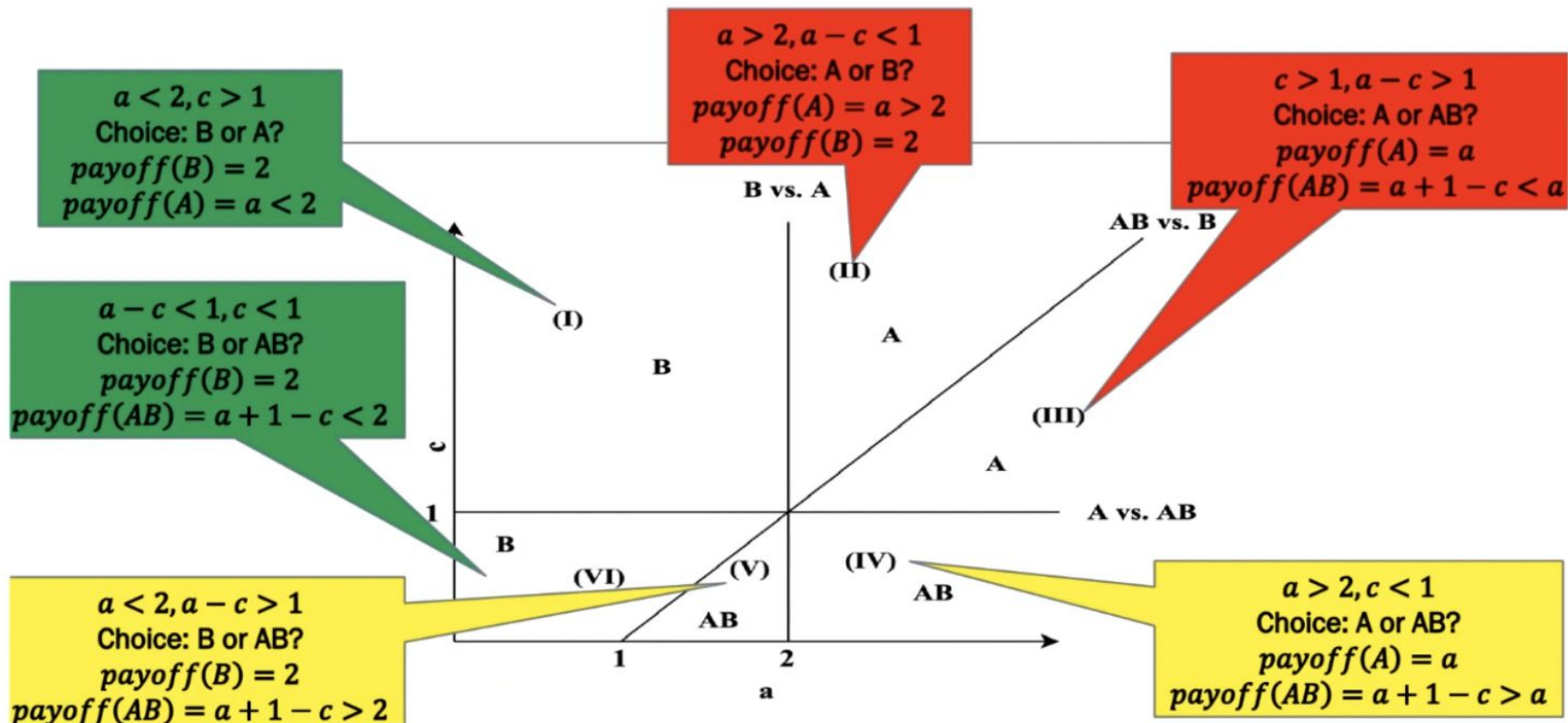
Three possible options for node u

1. Adopt Behavior A; Payoff = $a + 0 = a$
2. Adopt Behavior B; Payoff = $1 + 1 = 2$
3. Adopt Behavior AB; Payoff = $a + 1 - c$, if $\max(a, 1) = a$

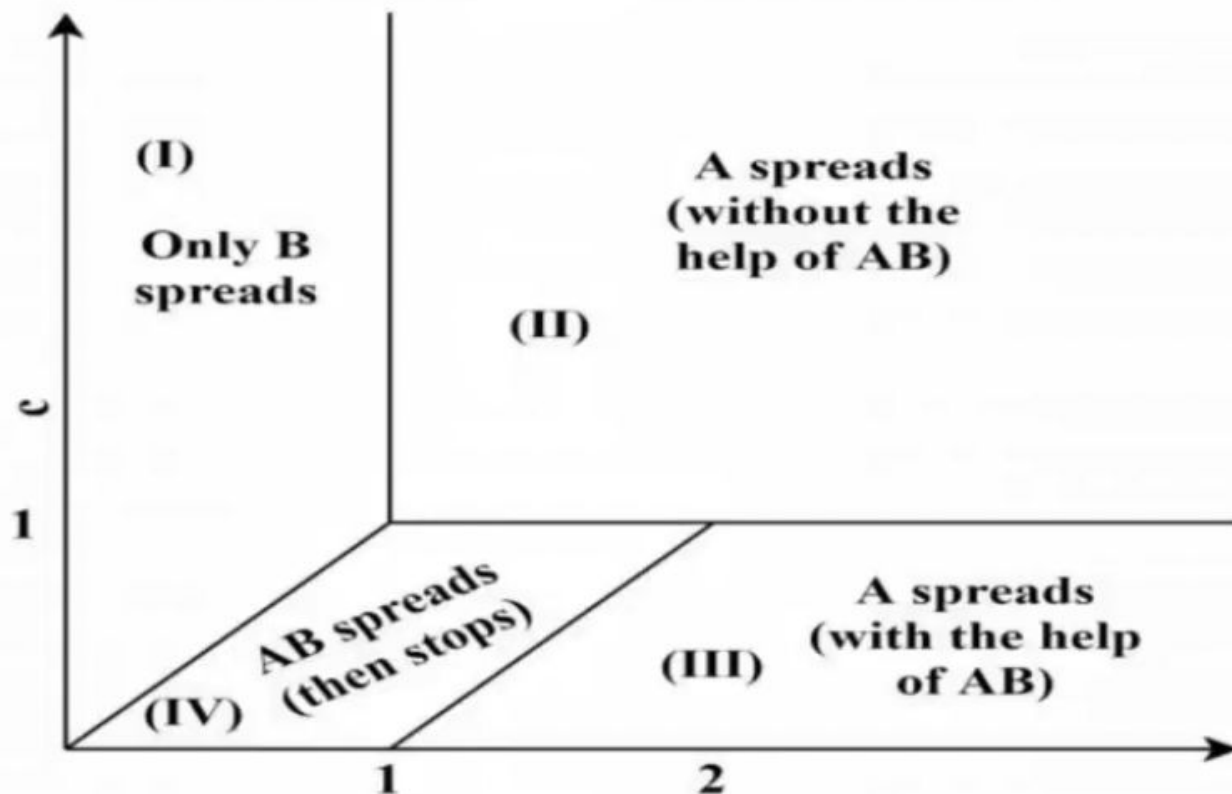
Breakpoint Equations:

- a. B versus A: $a = 2, a < 2$: Prefer strategy B; $a > 2$: Prefer strategy A
- b. AB versus B: $a - c = 1, a - c < 1$: Prefer strategy B; $a - c > 1$: Prefer strategy AB
- c. A versus AB: $c = 1, c < 1$: Prefer strategy AB; $c > 1$: Prefer strategy A

Generic Model: Case B



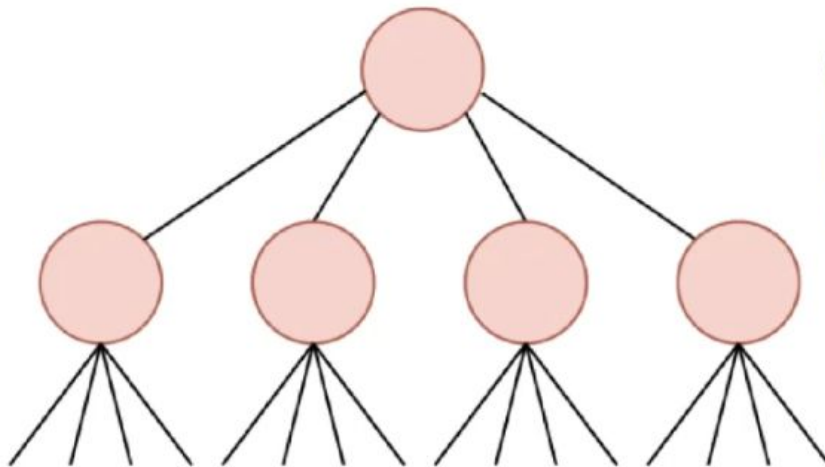
Generic Model: Combined



Decision-based Cascade Model: Limitations

- ☐ Cascade will continue to grow only when its growth is associated with the highest reward amongst each of the nodes
- ☐ In many real-world scenarios, such hard decision making criteria or payoff functions are not available
- ☐ Infection spreading mechanism of a virus
 - We can model the spread of the virus as a cascade
 - Cascade growth is not in the hands of the node.
- ☐ Alternative Approach (Probabilistic Cascade Model)

Probabilistic Cascade Model: Random Tree



A random tree with $d = 4$

- ❑ Basic assumptions
 - ❑ Person at the **root node** of the random tree is always infected
 - ❑ Each person in the random tree meets d new people. So, the random tree is a **d -nary tree**
 - ❑ Each person, on meeting an infected person, has the probability of getting infected as q ($q > 0$)
- ❑ For the virus to stay active and keep on spreading (cascade)
 - ❑ probability that a node at a depth h will be infected should be a positive real number
 - ❑ Same must hold for all h
$$\lim_{h \rightarrow \infty} P[\text{a node at depth } h \text{ is infected}] > 0$$
- ❑ The cascade would die out if
$$\lim_{h \rightarrow \infty} P[\text{a node at depth } h \text{ is infected}] = 0$$

Probabilistic Cascade Model: Random Tree

- If p_h be the probability of a node being infected at level h , then

$$p_h = 1 - (1 - q \cdot p_{h-1})^d$$

- The recurrence relation can have the following functional form:

$$f(x) = 1 - (1 - qx)^d$$

- The properties of f

- $f(x)$ is monotonic function
- $f'(x)$ is non-increasing
- $f'(x)$ is monotonic, non-increasing in $[0,1]$

- $f(0) = 0$ and $f'(0) = q \cdot d$

Probabilistic Cascade Model: Random Tree

- ☐ Since $f'(x)$ is monotonic non-increasing, $f'(x) \leq q \cdot d$
- ☐ For epidemic to die out, $f(x) < x \Rightarrow q \cdot d < 1$
- ☐ The quantity $q \cdot d$ is called Reproductive number in the literature, denoted R_0
- ☐ If $R_0 \geq 1$, the epidemic grows in an exponential manner
- ☐ If $R_0 < 1$, the epidemic spread reduces constantly and eventually dies out
- ☐ two methods to contain the spread of the epidemic
 - ☐ reduce the value of $d \Rightarrow$ keep the already-infected nodes in isolation
 - ☐ reduce the value of $q \Rightarrow$ reduce transmission rate by promoting better hygiene practices

R_0 shows how quickly a disease spreads.

- Measles: ~12–18 (very contagious)
- COVID-19 (early): ~2–3



Work Integrated Learning Programmes

Anomaly detection



Famous Survey papers, Books

- Graph based Anomaly Detection and Description: A Survey (600+ citations)
- Anomaly detection in dynamic networks: a survey (~200 citations)

Work Integrated Learning Programmes

Introduction

- ◆ We are drowning in the deluge of data that are being collected world-wide, while starving for knowledge at the same time.
- ◆ Anomalous events occur relatively infrequently
- ◆ However, when they do occur, their consequences can be quite dramatic and quite often in a negative sense



**"Mining needle in a haystack.
So much hay and so little time"**

Introduction

- Anomaly is a pattern in the data that does not conform to the expected behaviour.
- Also referred to as **outliers, exceptions, peculiarities, surprises**, etc.
- The branch of data mining concerned with discovering rare occurrences in datasets is called ***anomaly detection***.
- This problem domain has numerous high-impact.

Real World Anomalies

- Credit Card Fraud
 - An abnormally high purchase made on a credit card
- Cyber Intrusions
 - A web server involved in *ftp* traffic
- Fake followers/retweeters
 - Blackmarket based activities

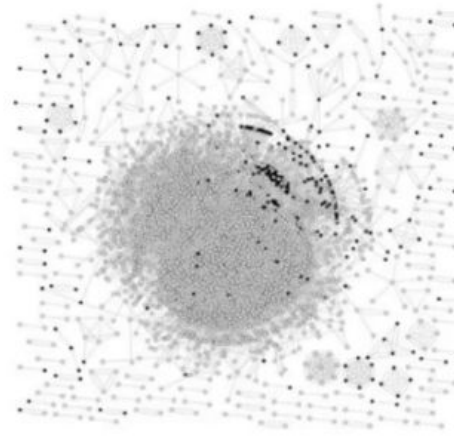
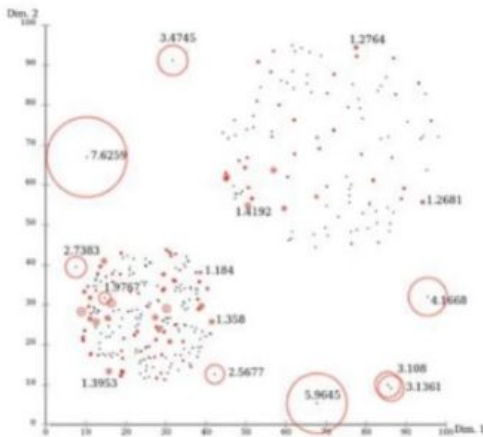


Other Applications

- Calling card and telecommunications fraud
- + Auto insurance fraud
- Email and Web spam
- Opinion deception and reviews spam
- Auction fraud
- Tax evasion
- Customer activity monitoring and user profiling
- Click fraud
- Securities fraud
- Malware/spyware detection
- False advertising
- Image/video surveillance

Outliers vs. Graph Anomalies

- Most outlier detection techniques treat objects as points lying in a multi-dimensional space independently.
- In contrast, they may exhibit inter-dependencies



In a reviewer-product review graph, the extent a reviewer is fraudulent depends on what ratings s/he gave to which products

- as well as how other reviewers rated the same products

Challenges/Opportunities: Ill-defined problem

- No unique definition for the problem of anomaly detection exists.
- The definition becomes meaningful only under a **given context or application**.

Definition: (Hawkins' Definition of Outlier, 1980)

"An outlier is an observation that differs so much from other observations as to arouse suspicion that it was generated by a different mechanism."