Using Players' Gameplay Action-Decision Profiles to Prescribe Training

Reducing Training Costs with Serious Games Analytics

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GAMES VS. SERIOUS GAMES

- Serious Games : Non-entertainment games (also, games4change, games4health, games for training, game-based learning.)
- Serious Games are ***TOOLS***
- Can be used for many purposes:
  - human performance training (workplace),
  - game-based learning (education)
  - policy change (social)
- Need to maximize values of SG for **clients**!!

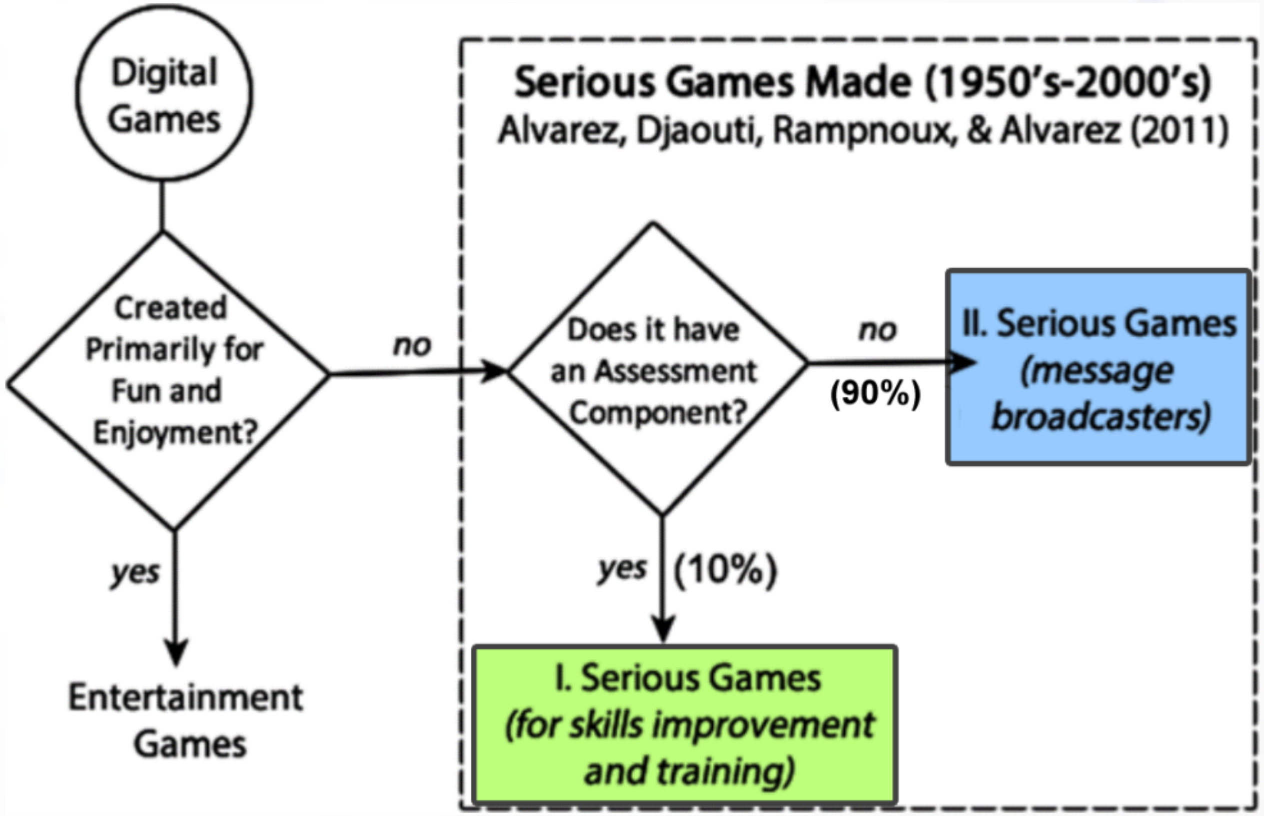
MORE TERMS

- **Acton-Decision Data** : Most player generated *in-game* data are consisted of actions (result of decision-making process), hence: *action-decision* data
- **Profiles** : Binning of action-decision data into groups based on certain 'identifying features'.
- **Training** : especially that of human performance (AIM: ***improve*** human ***performance*** *over time*).
- **Prescribe** : When to ______, how much to ______, what to _____ (procedure to follow), ***OR NOT***
- **Reducing training cost** :A desired outcome for many training organizations (maximizing values of serious games for your customers!)
  - VS. Monetization *(maximizing value of serious games for the developing company)*
- **Serious Games Analytics** : creating insights for ***performance*** measurement, assessment, and ***improvement*** (also include information ***visualization*** and ***predictive*** analytics)

GAMES VS. SERIOUS GAMES

- S.G. -- *tools* for human performance training (workplace) and game-based learning (education)
- Serious Games Analytics – predict, measure, assess, and improve performance; as well as reporting/visualization

- *How about diagnostics* to 'prescribe training'
  - Who should receive training?
  - When to provide training?
  - How much content should be included or withheld?



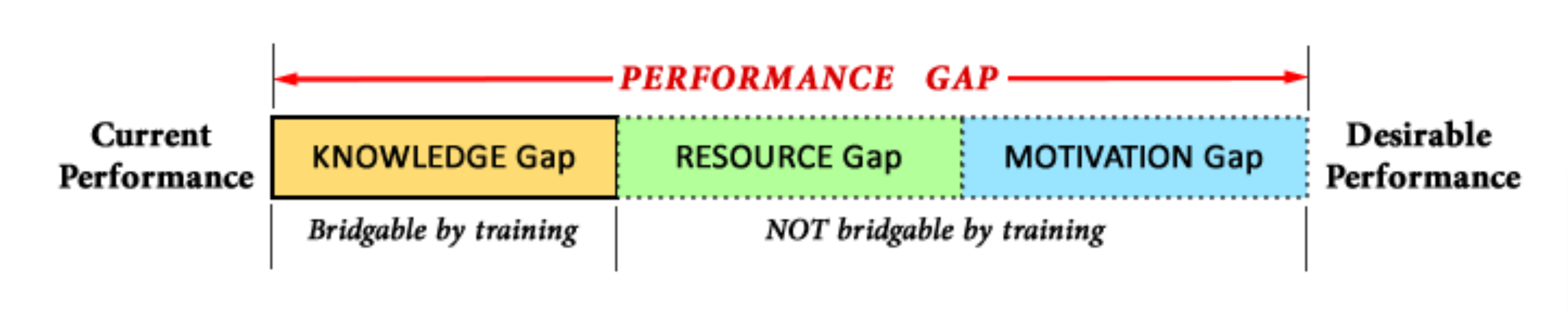
MAXIMIZING THE VALUE OF PLAYER DATA

- **Motivation: Use *Serious Games Analytics* to reduce training cost.**
  - Improve performance (reduce cost) through Serious Game Analytics.
- **Why?**
  - **25% of Global Fortune 500 companies use serious games for training**.

- ***Information Trails*** (our system) contains BOTH telemetric data capturing and visualization
- ***Performance Report Tracing assistant (PeTRA)***: *ad hoc* (real-time) and *post hoc* (after action) reporting

PERFORMANCE AND "PERFORMANCE GAP"

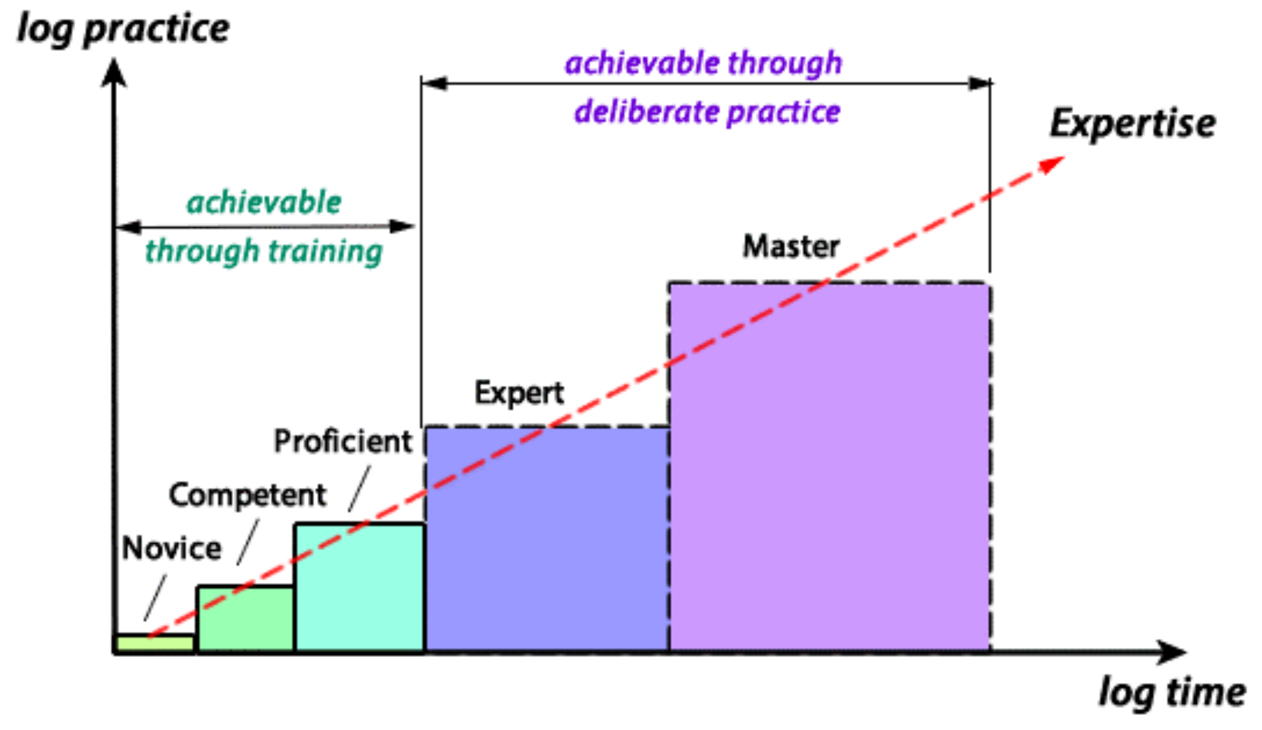
- Before improving performance, you must first understand performance gap.
- According to literature in the field of **Instructional Design & Technology**, a *Performance Gap* is caused by the combination of three factors:



- Only the ***Knowledge Gap*** is bridgeable through training, but not the *Resource* and *Motivation Gaps*.

SKILL ACQUISITIONS TOWARDS EXPERTISE

- **Five-level Model of Expertise** (Dreyfus & Dreyfus, year)
- Only the first three levels can be achievable through *training*
- Expert and Master are only attainable through long period of ***deliberate practice*** (up to 10 yrs/10 000 hrs)



THE NEEDS OF ORGANIZATIONS FOR EXPERTISE

- Majority of workforce in the lower levels: Novice, Competent, and Proficient.
- Expert/ Master 'role models' are very valuable but RARE assets → need time to grow
- New hires enter at absolute Novice level to some degrees of Proficient.
- Deliberate practice is severely lacking in organizational (F2F) training → achievable through technology-enhanced training (e.g., serious games, simulation, etc).

WHY PRESCRIBE TRAINING?

- **Maximized Players' Data for Value:** Players' in-game actions and decisions can be measured in lieu of performance *in situ* serious games and visualized as insights
  - For PREDICTING performance and PRESCRIBING training
- If we can *predict players' performance*, we can *prescribe training* → Identifying who, what, and when to train, or *not* to train.
- Evidence-based training prescriptions:
  - ***Under-training*** puts organizations at high risk (workers' mistakes → liabilities)
  - ***Just-right training*** (common sense approach → but how much is just right?)
  - ***Over-training*** (higher cost → Seriously, why?)

WHY PRESCRIBE *OVER*-TRAINING?

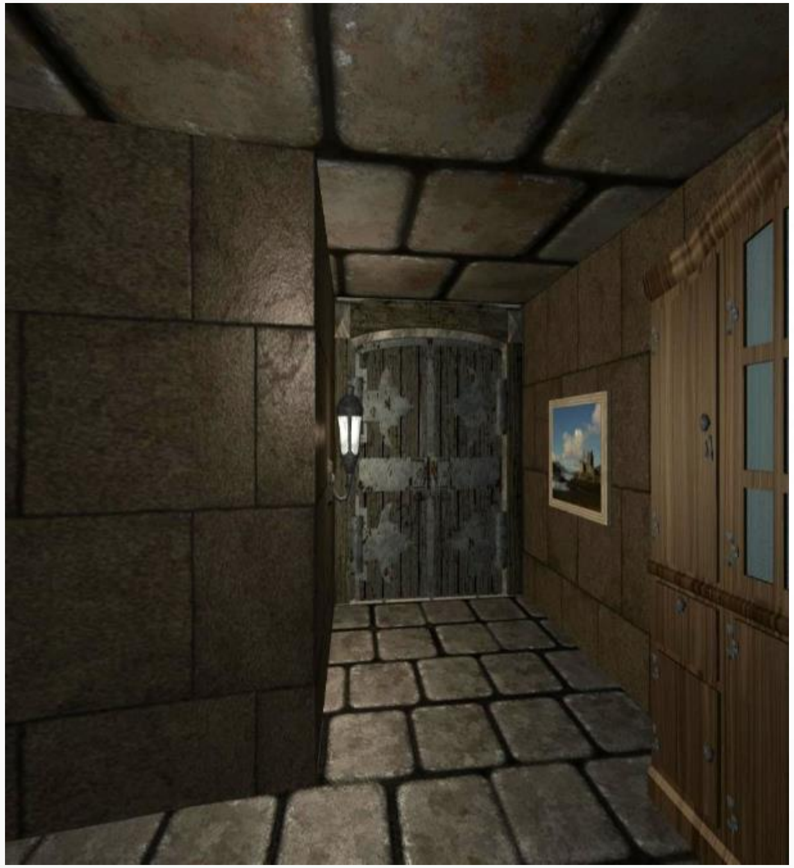
Research shown **Over-training** is necessary to:

- Achieve automaticity (efficiency and quality assurance)
- Maintain ***adequate*** performance during ***high-stress*** situations
  - Athletes (Olympics)
  - Pilots (emergency landing)
  - First Responders (disaster training), Surgeons, etc.
- ***Training prescription*** is a relatively untapped area, more research needed to determine what to prescribe

INFORMATION TRAILS

Loh, Anantachai, Byun, & Lenox (2007)

Gameplay action-decisions data (Course of Actions)



Telemetry

Data stored in remote database

Visualized

Performance Tracing Report Assistant (PeTRA)

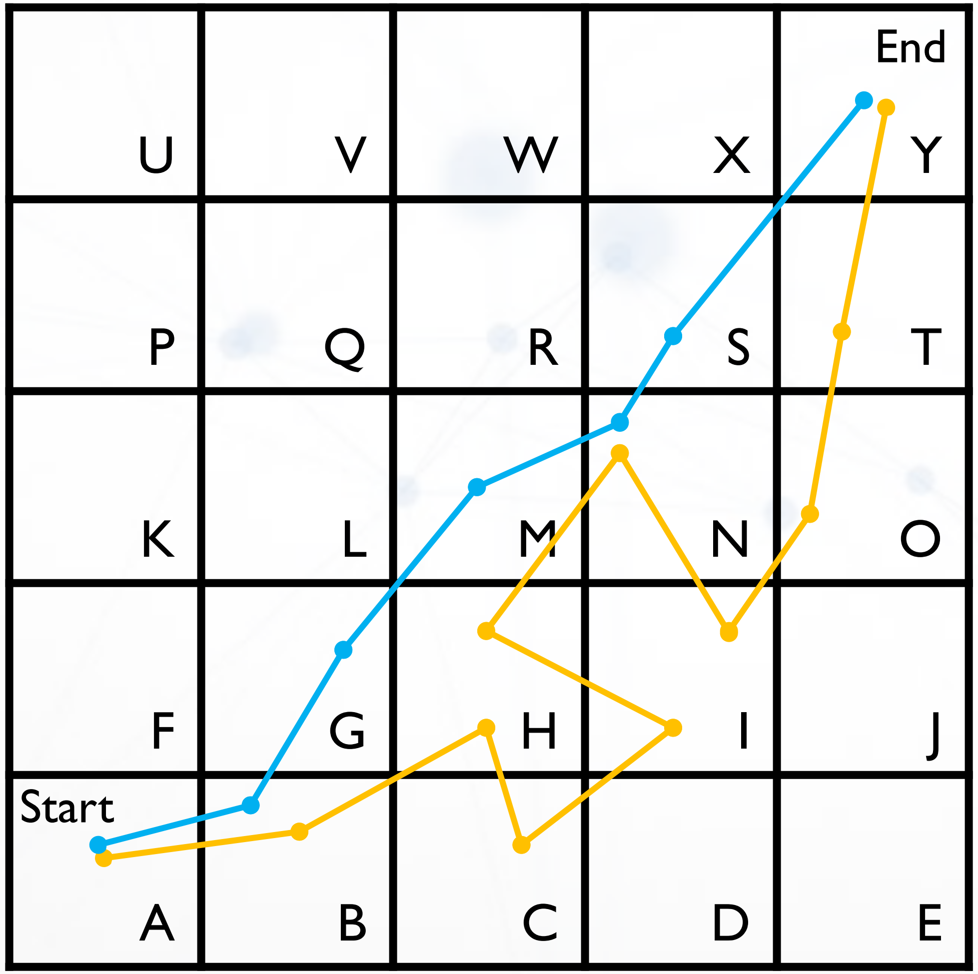
SIMILARITY MEASURES

Loh & Sheng (2013, 2014)

- *Please see our other paper on how this can be done (Loh & Sheng, 2013; 2014).*
- *Competency* is characterized by an observable and demonstratable *course of actions* (COAs) during problem-solving (Dreyfus & Dreyfus, 1980).
- Steps:
  1. Traced players' Course of Actions (i.e., gameplay action-decision data) telemetrically
  2. Converted COAs into strings for similarity comparison
  3. Pairwise comparison: Players (any levels) against the Expert baseline (ideal route)
     - Expert can be anyone you name (depending on your purpose)

PLAYERS' COURSE OF ACTIONS (COA)

Loh & Sheng (2013, 2014)



Convert players' movement to COAs:

Expert (Ideal route):

ABGMNSY

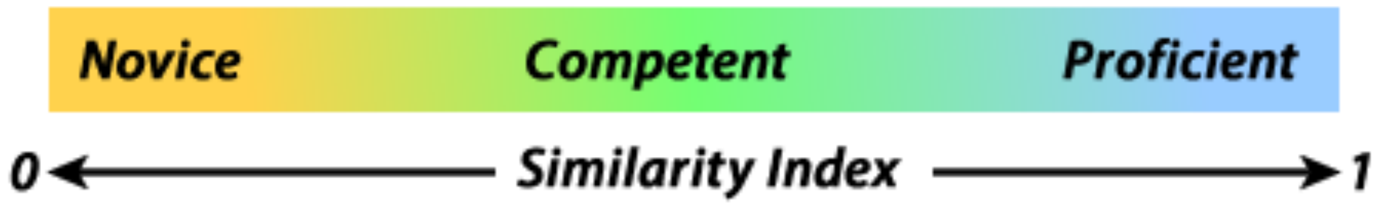
Player (novice/unknown, extra movements):

ABHCIHNIOTY

DIFFERENTIATING EXPERT NOVICE BY SIMILARITY

Loh & Sheng (2013, 2014)

- Pairwise string similarities comparison (in our study, Cosine similarity)
- Similarity coefficient (ranges from 0 – 1, or, 0% – 100%)
  - value of 1: is identical to the expert/ideal route.
  - value of 0: furthest distance (or, most dissimilar) from expert route.



- Further Readings: Additional similarities (Dice, Jaccard, etc), see Loh & Sheng (2013, 2014)
- Efficiency comparison of 5 similarities, see Loh, Li, & Sheng, 2016

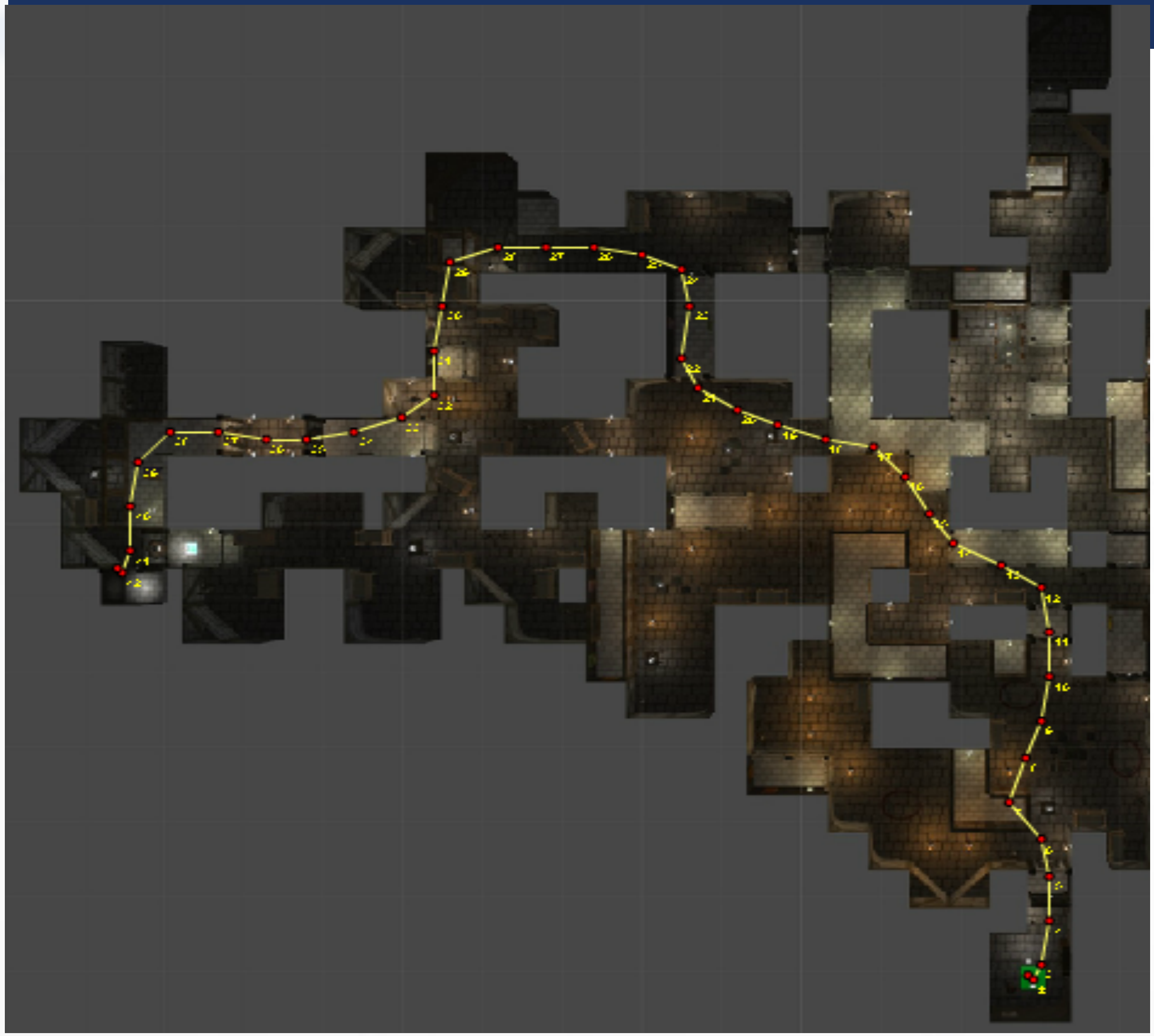
WHAT IF: MULTIPLE EXPERTS' ROUTES?

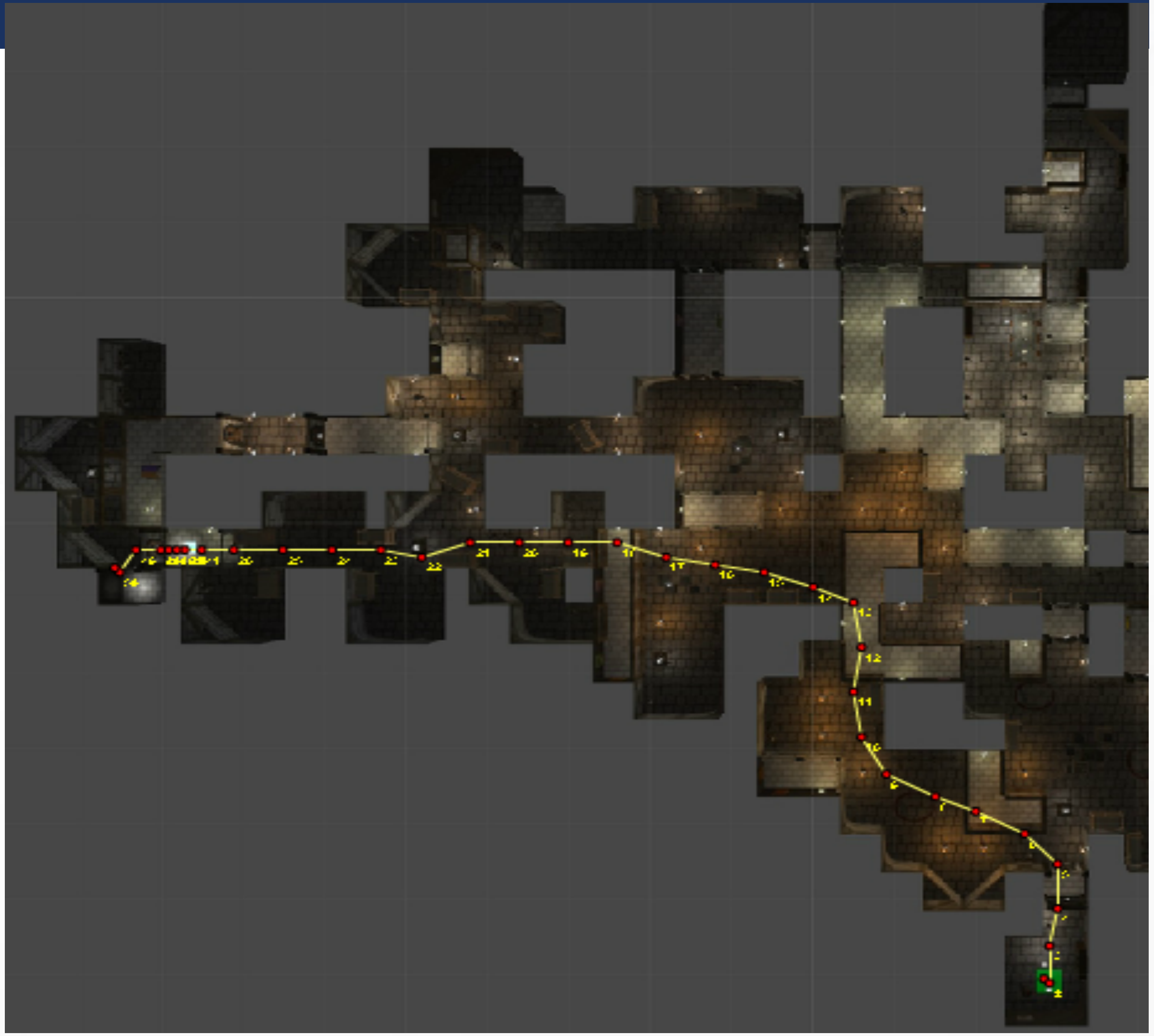
- *Please see our other paper (Loh & Sheng, 2014)*
- Sometimes, multiple experts may be present in a training scenarios.
- You cannot "Average" expertise performance → it is no longer expertise.
- Instead of 1 (player) to 1 (expert) similarity comparison, players' routes need to be compared to multiple expert routes simultaneously.
- Loh & Sheng (2014) developed a method called Maximum Similarity Indices (MSI) to compensate for this situation to obtain players' 'true' similarity score.

METHOD

- In-house game (Unity3D Maze)
- 16 participants (student volunteers)
- Two critical routes, both are 'correct'
  - RouteA – Longer
  - RouteB – Shorter, but with obstacle
    - "Pressure Plate" puzzle (take time to solve, but yield better long-term performance)

LONG VS. SHORT (CRITICAL) ROUTE





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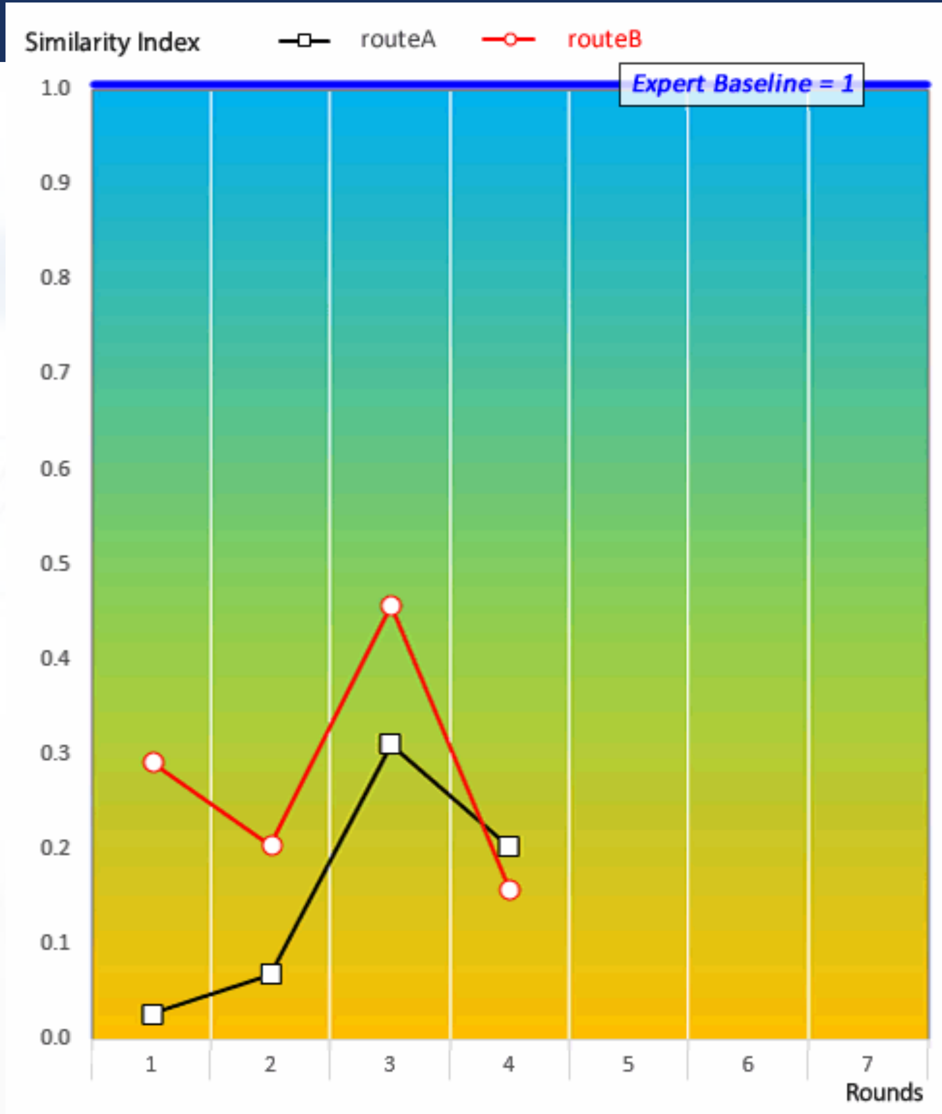
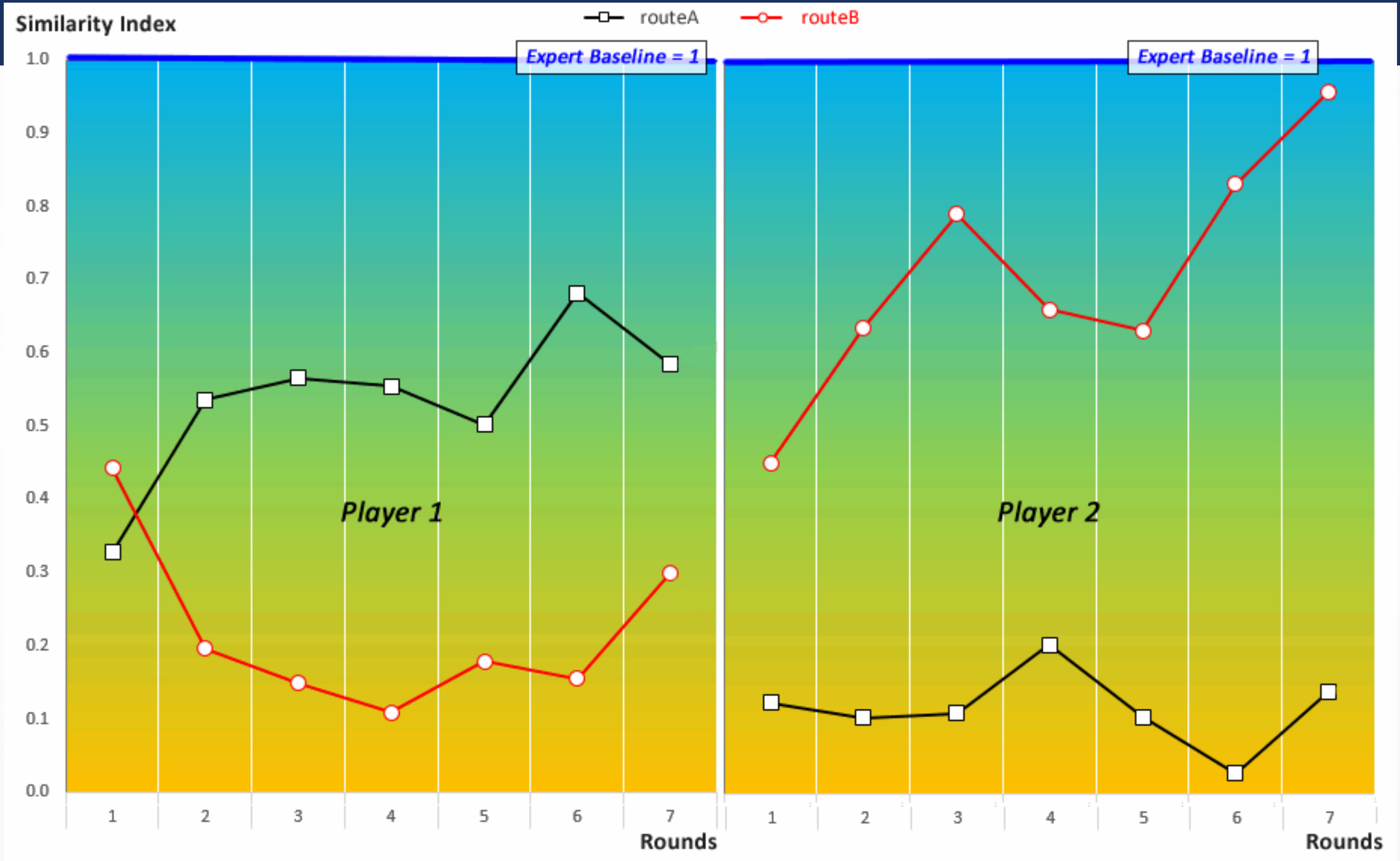
- R to calculate Cosine similarity : “*stringdist*” package (van der Loo, 2006).
- Maximum Similarity Index (MSI) needed for some profiles.
- Visualization of COAs reveal three patterns of problem-solving strategies
- We name this *Gameplay Action-Decision* (GAD) profiles.

GAME ACTION-DECISION PROFILE 3: QUITTER

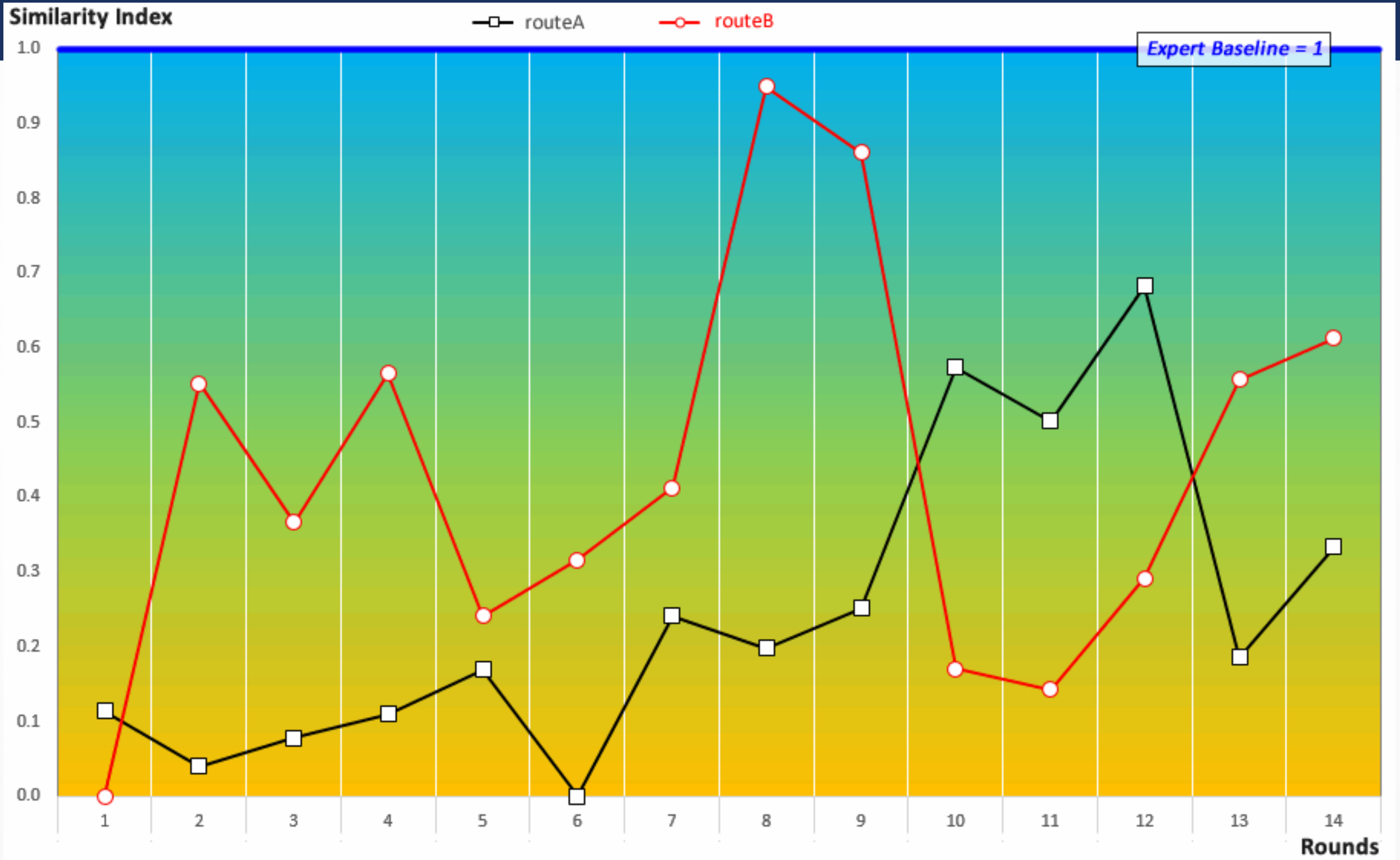
- Players who quit in less than 5 rounds.



GAME ACTION-DECISION PROFILES: FULFILLER

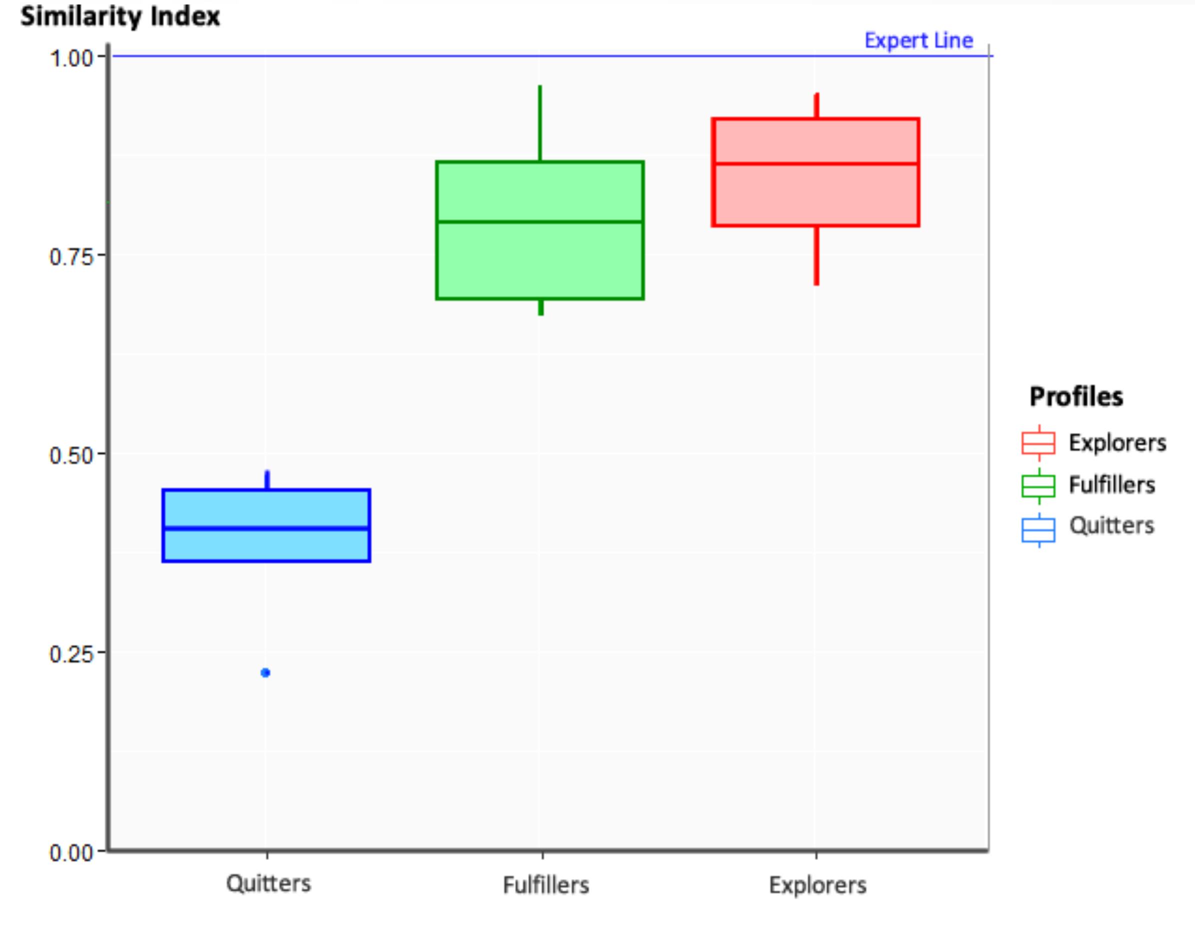


GAME ACTION-DECISION PROFILES: EXPLORER



PERFORMANCE DIFFERENCES BY PROFILES

- *t*-test (*α*-level = 0.01), difference between three groups.
- Statistically significant difference between Quitters and the two other profiles ($p < 0.0001$ for both cases).
- No detectable statistically significant difference between the Explorers and Fulfillers ($p = 0.805$).
- Performance/similarity scores:
  - Quitters (M = 0.399, SD = 0.068)
  - Fulfillers (M = 0.794, SD = 0.117)
  - Explorers (M = 0.846, SD = 0.108)
  - The highest score (0.959) belonged to a Fulfiller.



CONTRIBUTIONS OF GAD PROFILES

- Gameplay Action-Decision (GAD) profiling is data-driven and evidence-based
- GAD profiles can be used to visualize how people make decisions *in situ* virtual training habitats
- Open ways to decision-making and training research using similarity in game data science for corporate use → Prescribing Corrective, Regular, Over-Training
- Maximizing player value in gameplay data through deliberate practice:
  - Increase proficiency under normal circumstances
  - Maintain adequate performance under high-stress situations (e.g., disaster training).
  - Encourage workers to learn new decision-making strategy (Fulfiller⇔Explorer)

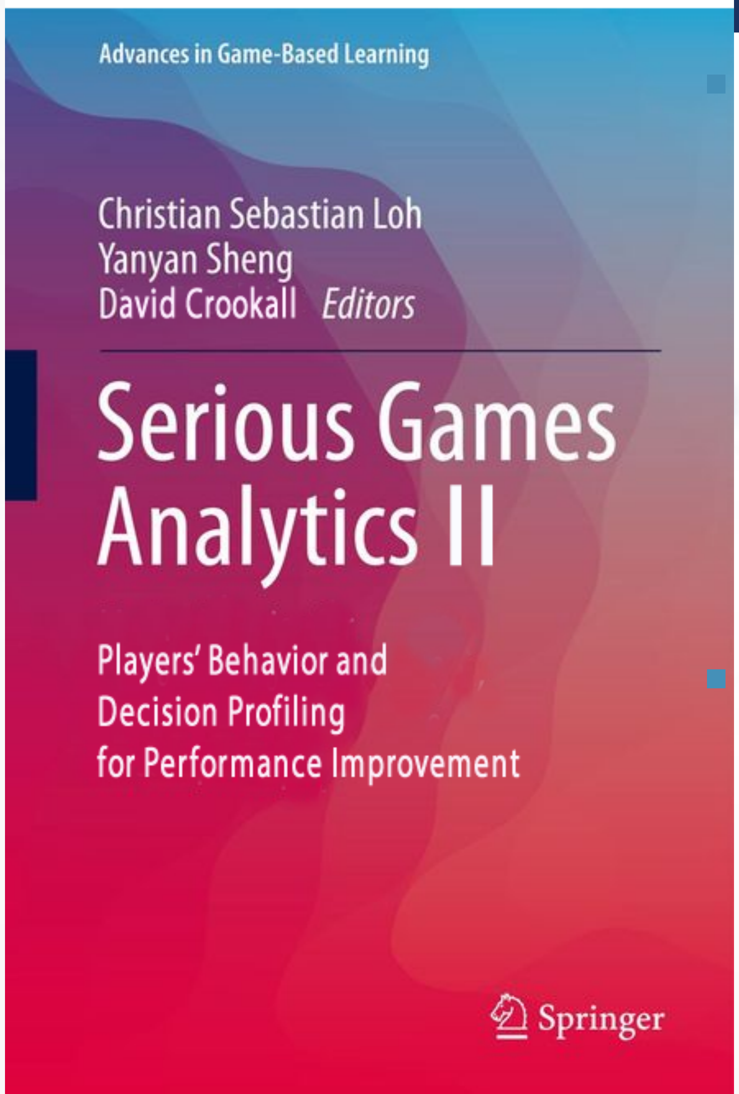
CONCLUSION

- Many potential applications for Gameplay Action-Decision (GAD) profiling, reducing training cost is just one obvious application in training performance improvement.

Q&A

GOT QUESTIONS?

SERIOUS GAMES ANALYTICS II (2018) -- *CALL FOR CHAPTER*



Behavioral & Decision Analytics Profiling for Performance Improvement

- Military, Healthcare, and Business training industry
- (Serious) game design improvement / monetization
- Behavioral and procedural learning / training (e.g., sports, surgery, rehabilitation, game-based training)
- Prescription of over-training, corrective training
- Cross profile training

Methodologies and Applications

- Identifying users' action-behaviors and decision-making information
- Modeling temporal behavior and decision-making behavior
- Efficient techniques for online/real-time behavioral processing

http://www.csloh.com/SEGA