Maximizing the potential of digital games for understanding skill acquisition

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These slides:
Abstract

Gaming is a domain of profound skill development. Players’ digital traces create data that track the development of skill from novice to expert levels. We argue that existing work - including my own! - although promising, has yet to take advantage of the potential of game data for understanding skill acquisition, and that to realize this potential, future studies can use the fit of formal learning curves to individual data as a theoretical anchor. Learning-curve analysis allows learning rate, initial performance, and asymptotic performance to be separated out, and so can serve as a tool for reconciling the multiple factors that may affect learning. I will illustrate these points with data from a large data set of player performances from a causal game.

Limitations in the study of learning


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An idea!

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@tobybarnes

preloaded.com

http://axon.wellcomeapps.com/
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Example player data (id = 123)
Example player data (ids 97 to 106)
Example player data for people who played more than 15 times.
The graph shows the average score as a function of attempt number. The data points are plotted on a logarithmic scale, with the average score ranging from $10^4$ to $3 	imes 10^4$. The attempt number ranges from 1 to 10. The total number of data points is $n=854064$. These slides: http://bit.ly/tom-talks
Not just data...need theory

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Practice: amount

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"at least 10,000 hours of dedicated practice (about 6 years of playing chess 5 hours a day) are required to attain the highest levels of performance" (Kahneman, 2011, p238).

The “Ten Thousand Hours Rule”


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The “Ten Thousand Hours Rule”


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Expert

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Destiny

~120 million active players


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Learning curves as theoretical anchor

Fig. 1. The learning curve as a theoretical anchor for studies of skill acquisition in games. This figure shows a simple, three-parameter, power-law learning curve: Performance, $f(t)$, is a function of practice, $t$; an upper limit, $u$; the learning gain, $a$, which defines how far initial performance is from the upper limit; and the learning rate, $c$. The notation follows Steyvers and Benjamin (2019).

Code for implementing this learning-curve function, and fitting it to data, is available on OSF, at https://osf.io/fvm8s/.
Fit params: $u = 35719$, $a = 26175$, $c = -0.24$

- asymptote
- learning rate
- initial performance

[Observed data vs. fit $y = u - ax^c$]

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Maximizing the Potential of Digital Games for Understanding Skill Acquisition

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Abstract
Gaming is a domain of profound skill development. Players’ digital traces create data that track the development of skill from novice to expert levels. We argue that existing work, although promising, has yet to take advantage of the potential of game data for understanding skill acquisition, and that to realize this potential, future studies can use the fit of formal learning curves to individual data as a theoretical anchor. Learning-curve analysis allows learning rate, initial performance, and asymptotic performance to be separated out, and so can serve as a tool for reconciling the multiple factors that may affect learning. We review existing research on skill development using data from digital games, showing how such work can confirm, challenge, and extend existing claims about the psychology of expertise. Learning-curve analysis provides the foundation for direct experiments on the factors that affect skill development, which are necessary for a cross-domain cognitive theory of skill. We conclude by making recommendations for, and noting obstacles to, experimental studies of skill development in digital games.

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Stafford & Haasnoot (2017)
Stafford & Haasnoot (2017)

The graph illustrates the average score across different conditions of practice and spacing.

- **Practice (1-15 attempts)**: A close-up look at the improvement in scores for 1-15 attempts shows a steady increase.
- **Spacing (0-60 minutes)**: The graph indicates a moderate improvement over time with spaced practice.
- **Initial Performance (percentile)**: The red triangles represent initial performance, showing a sharp increase at the start, followed by a plateau.
Learning curves as theoretical anchor

Games tremendous opportunity for studying skill acquisition, but the huge, messy, data must be probed with

- formal fitting of learning curves
- experiments for strong causal inference


Curve fitting code in R and Python: https://osf.io/fvm8s/.

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Learning curves as theoretical anchor

Experiments with games need:

- Entertainment value / intrinsic motivation
- Challenge / modifiable difficulty
- Scoring / clear outcome measure
- Benchmarks / absolute or relative
- Components / identifiable and quantifiable
- Out of game measures / e.g. Kokkinakis et al. (2017)


Curve fitting code in R and Python: https://osf.io/fvm8s/.

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END

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Lots more to do

Does it matter *how* you practice?
  - spacing? variability? exploration?

Can we predict the level of skill someone will eventually acquire?
  - How? How soon?

How to escape plateaux in learning?
We’re going to do it the right way
Skill learning in an online game

Contributors: Tom Stafford

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Category: Project

Description: Data from the game Axon and analysis code. See Stafford, T. & Dewar, M. (2014). Tracing the trajectory of skill learning with a very large sample of online game players. Psychological Science, 25(2) 511-518. and Stafford & Haasnoot (in preparation)