# Deconstructing the Filter Bubble: User Decision-Making and Recommender Systems

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# Introduction

Consequences of RS on user consumption choices?

**Within user: Filter Bubbles**

Users consume items in increasingly narrow portion of product space

**Across users: Homogenization**

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**This paper**

Economic model to explain empirically observed dynamics

RS's influence on decisions and its implications for design

# Our Model

1. Users **sequentially** consume **small set of items from large choice set**

2. Users are **uncertain** about item's true valuations
   - Users have *beliefs* about items they haven't consumed yet
   - Users potentially *risk-averse*

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   - Draws from distinct Gaussian distributions

   - RS reveals the common-value component

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Evaluate model via simulation over grid of parameters

# Illustrative Example
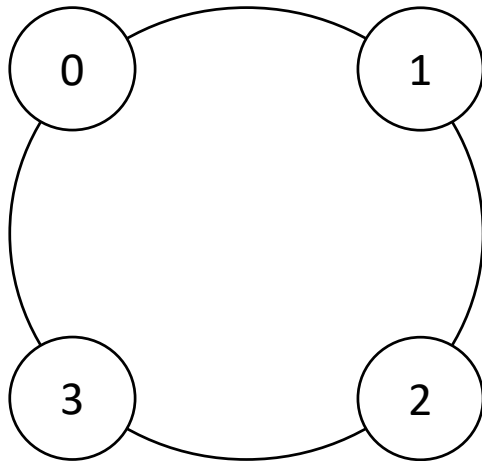
# Illustrative Example

$$\mu = \begin{pmatrix} \mathbb{E}[x_0] \\ \mathbb{E}[x_1] \\ \mathbb{E}[x_2] \\ \mathbb{E}[x_3] \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \Sigma = \sigma^2 \begin{pmatrix} \rho^0 & \rho^1 & \rho^2 & \rho^0 \\ \rho^1 & \rho^0 & \rho^1 & \rho^2 \\ \rho^2 & \rho^1 & \rho^0 & \rho^1 \\ \rho^1 & \rho^2 & \rho^1 & \rho^0 \end{pmatrix}$$

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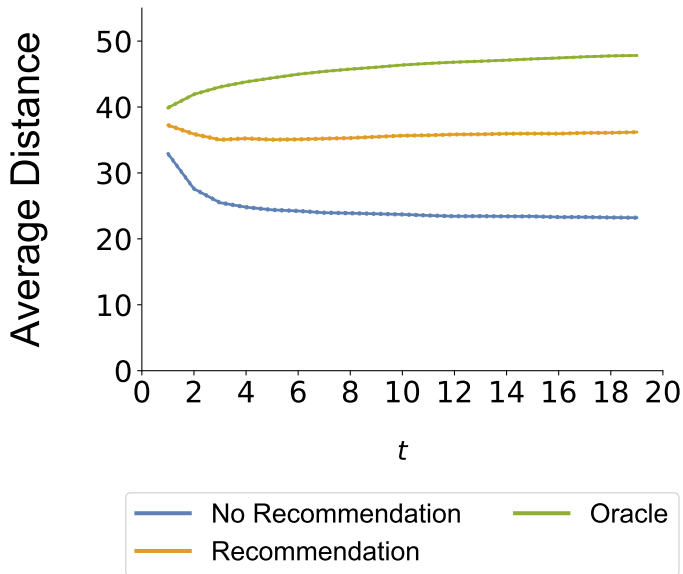
Realization of utility for item 0 is $y$, then updated beliefs are:

$$(\mu \mid x_0 = y) = \begin{pmatrix} \rho y \\ \rho^2 y \\ \rho y \end{pmatrix}, (\Sigma \mid x_0 = y) = \begin{pmatrix} \frac{3}{4} & \frac{3}{8} & 0 \\ \frac{3}{8} & \frac{15}{16} & \frac{3}{8} \\ 0 & \frac{3}{8} & \frac{3}{4} \end{pmatrix}$$

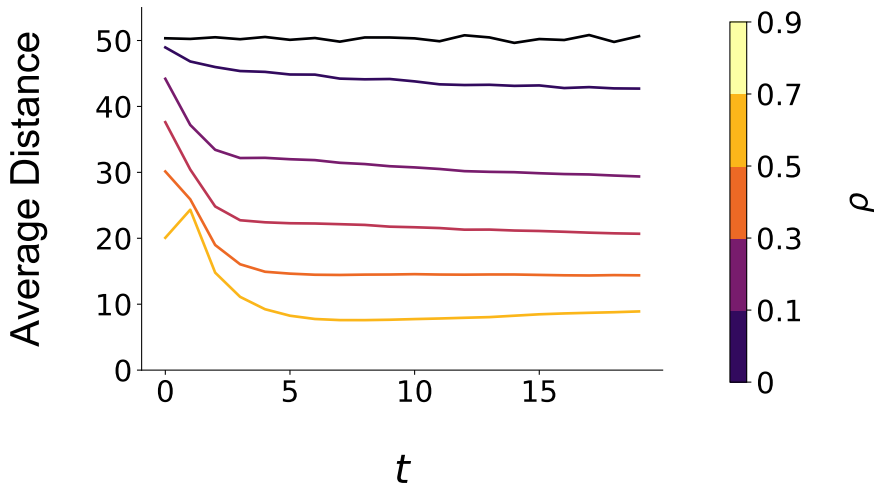If $y > 0$, then always consumes item 1 or 3

If $y < 0$, then consumes item 2 unless sufficiently risk-averse

# Filter Bubble Effects

Informational Spillovers Lead to Filter Bubble Effects

# Additional Results

**Filter bubble effects amplified by risk aversion**

Spillover reduces uncertainty

**Welfare Gains from RS**

Decreases as correlation between valuations increases

**Diversity vs. Welfare**

Without RS, diversity and welfare negatively correlated

With RS, diversity and welfare uncorrelated

**RS increases homogeneity**

Coordination around high common value component items

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**Our approach**:

Goal: pairing prediction with valuable information

Valuable information: steering user behavior towards better choices

Implications: Collect data not only on post-consumption ratings but
    also on pre-consumption *beliefs*