# Welcome

**"Recommender Systems: Beyond Machine Learning"**

**Joseph A. Konstan**

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Additional Info:

- Talk begins at the top of the hour and lasts 60 minutes
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# Recommender Systems: Beyond Machine Learning

Speaker: Joseph A. Konstan

Moderator: Bart Knijnenburg

# ACM Highlights

For Scientists, Programmers, Designers, and Managers:

- Learning Center - https://learning.acm.org
  - View past TechTalks & Podcasts with top inventors, innovators, entrepreneurs, and award winners
  - Access to O'Reilly Learning Platform – technical books, video courses, tutorials & case studies
  - Access to Skillsoft Training & ScienceDirect – vendor certification prep, technical books & courses
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- 2,200,000+ content readers
- 1,800,000+ DL research citations
- $1,000,000 Turing Award prize
- 100,000 global members
- 1160+ Fellows
- 700+ chapters globally
- 170+ yearly conferences globally
- 100+ yearly awards
- 70+ Turing Award Laureates

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- Queue Magazine - https://queue.acm.org
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# Recommender Systems: Beyond Machine Learning

Joseph A. Konstan

konstan@umn.edu

www.grouplens.org

# What are Recommender Systems?

» Tools that help narrow an otherwise overwhelming set of choices
  - Filters (categorize, select, or remove)
    - Common example, e-mail filters
    - Can have filters sift out inappropriate products
  - Recommendations
    - Often "product placement" or top-n lists
    - Direct to customer or via sales agent
  - Predicted values (e.g., hotel/restaurant stars)

# Level of Personalization

- » Generic Recommendation
  - Everyone receives the same; e.g. top sellers
- » Demographic Personalization
  - Targeted to people based on categories
- » Ephemeral Personalization (Context)
  - Matched to current activity (people who like ..)
- » Persistent Personalization (Profiles)
  - Matched to entire profile of activity/info

# Recommendation Approaches

- Manual (marketer) recommendations
  - "Sell the fish!"
- Simple summary statistics
  - Four-star hotel or cruise
- Product Associations
  - What items "go together"
- Content-based techniques
  - Learning from single-user profiles
- Collaborative techniques
  - Learning from other users' profiles too
- All of the above … advanced ML techniques

# Understanding the Computation

| | Hoop Dreams | Star Wars | Pretty Woman | Titanic | Blimp | Rocky XV |
|---|---|---|---|---|---|---|
| Joe | D | A | B | D | ? | ? |
| John | A | F | D | | F | |
| Susan | A | A | A | A | A | A |
| Pat | D | A | | C | | |
| Jean | A | C | A | C | | A |
| Ben | F | A | | | | F |
| Nathan | D | | A | | A | |

# User-User Collaborative Filtering

| | Hoop Dreams | Star Wars | Pretty Woman | Titanic | Blimp | Rocky XV |
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| Nathan | D | | A | | A | |

# Item-Based Collaborative Filtering

| | Hoop Dreams | Star Wars | Pretty Woman | Titanic | Blimp | Rocky XV |
|---|---|---|---|---|---|---|
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| John | A | F | D | | F | |
| Susan | A | A | A | A | A | A |
| Pat | D | A | | C | | |
| Jean | A | C | A | C | | A |
| Ben | F | A | | | | F |
| Nathan | D | | A | | A | |

# Item-Based Collaborative Filtering

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|---|---|---|---|---|---|---|
| Joe | D | A | B | D | ? | ? |
| John | A | F | D | | F | |
| Susan | A | A | A | A | A | A |
| Pat | D | A | | C | | |
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# But Today's Solutions Have Evolved ….

# Understanding the Computation

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|---|---|---|---|---|---|---|
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| Jean | A | C | A | C | | A |
| Ben | F | A | | | | F |
| Nathan | D | | A | | A | |

# Modern Recommender Systems

| | Hoop Dreams | Star Wars | Pretty Woman | Titanic | Blimp | Rocky XV |
|---|---|---|---|---|---|---|
| Joe | D | A | B | D | ? | ? |
| John | A | F | D | | F | |
| Susan | A | A | A | A | A | A |
| Pat | D | A | | C | | |
| Jean | A | C | A | C | | A |
| Ben | F | A | | | | F |
| Nathan | D | | A | | A | |

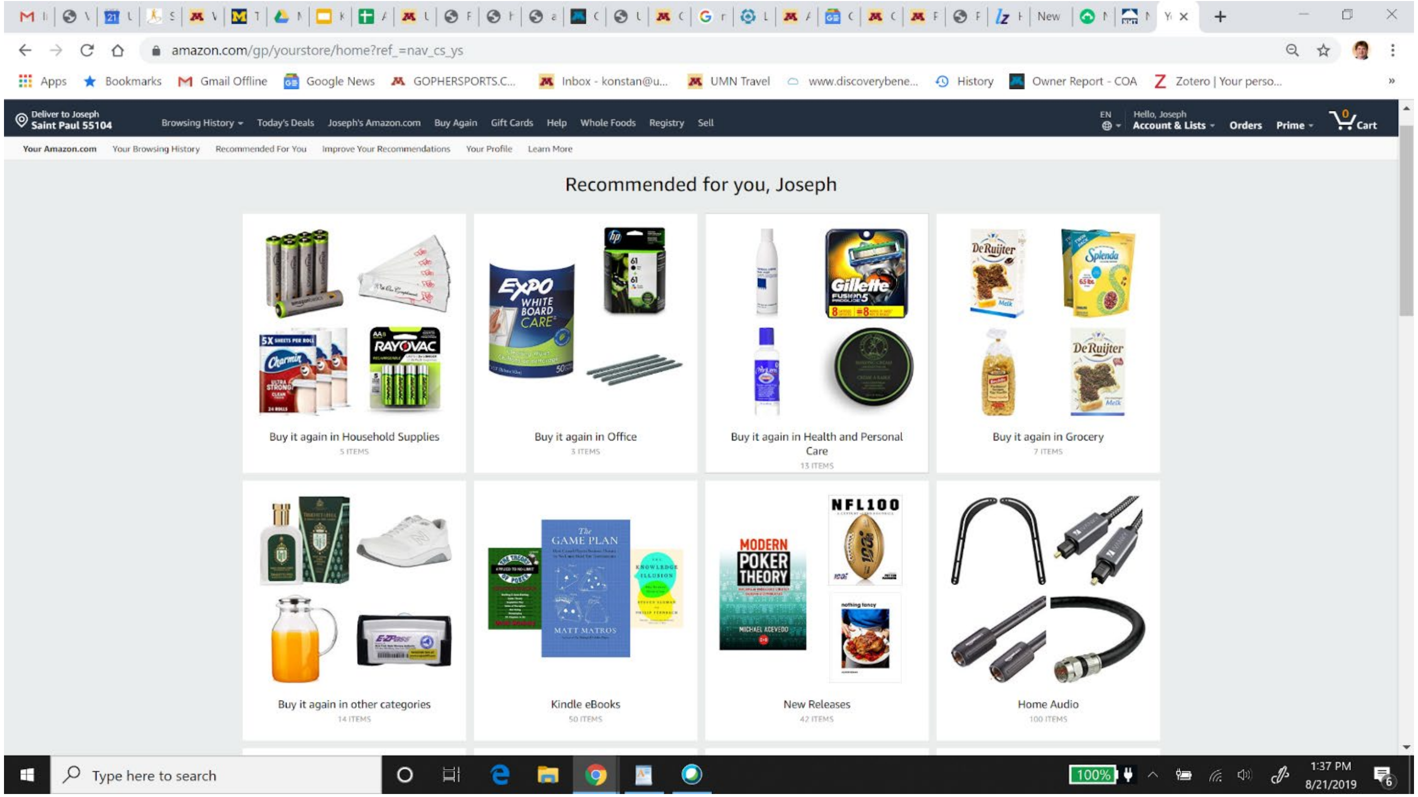
Latent Factor Models

Learning Models

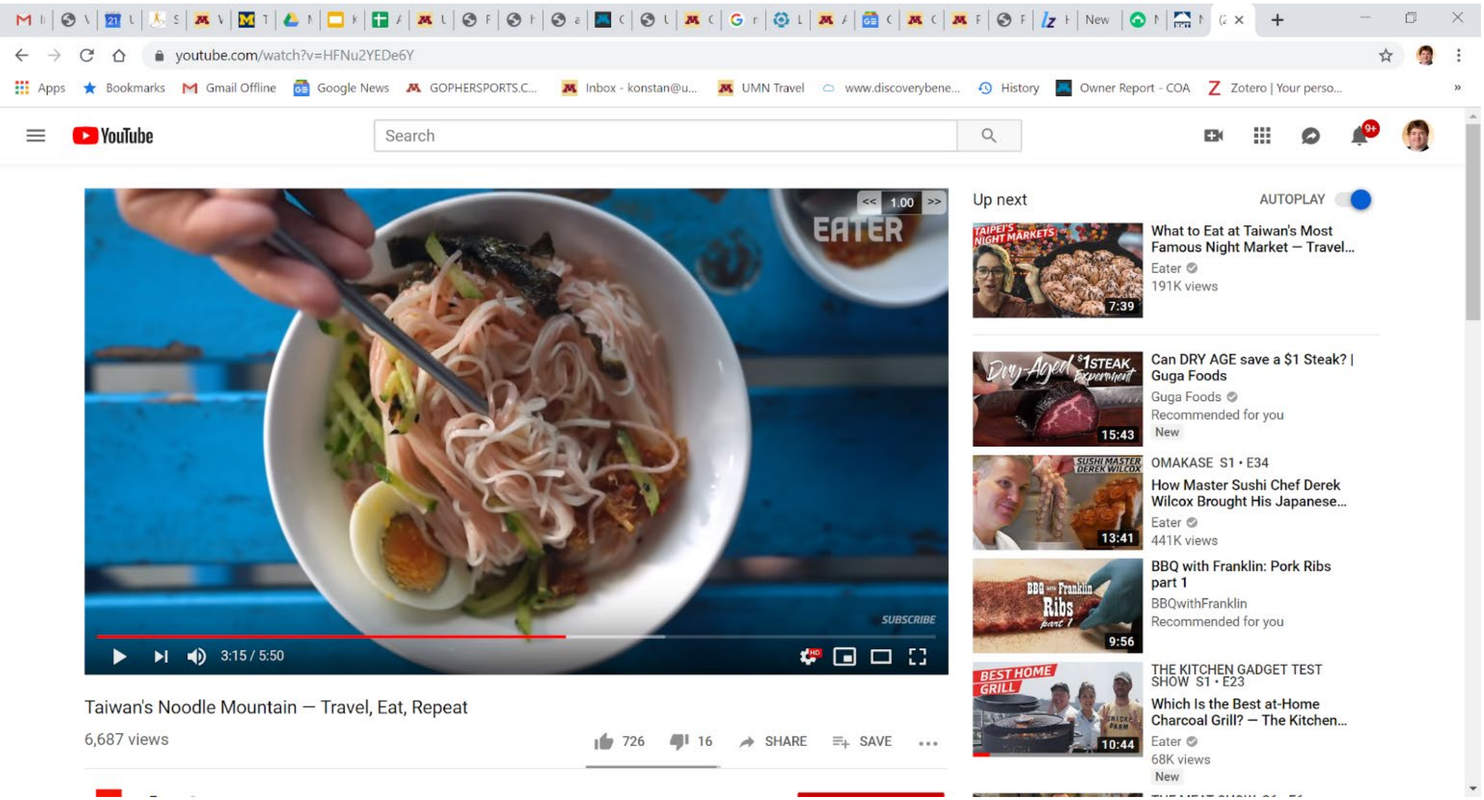
# So much technology, yet …

- Lousy recommendations are everywhere!

# What's wrong with these?



# What's wrong with these?



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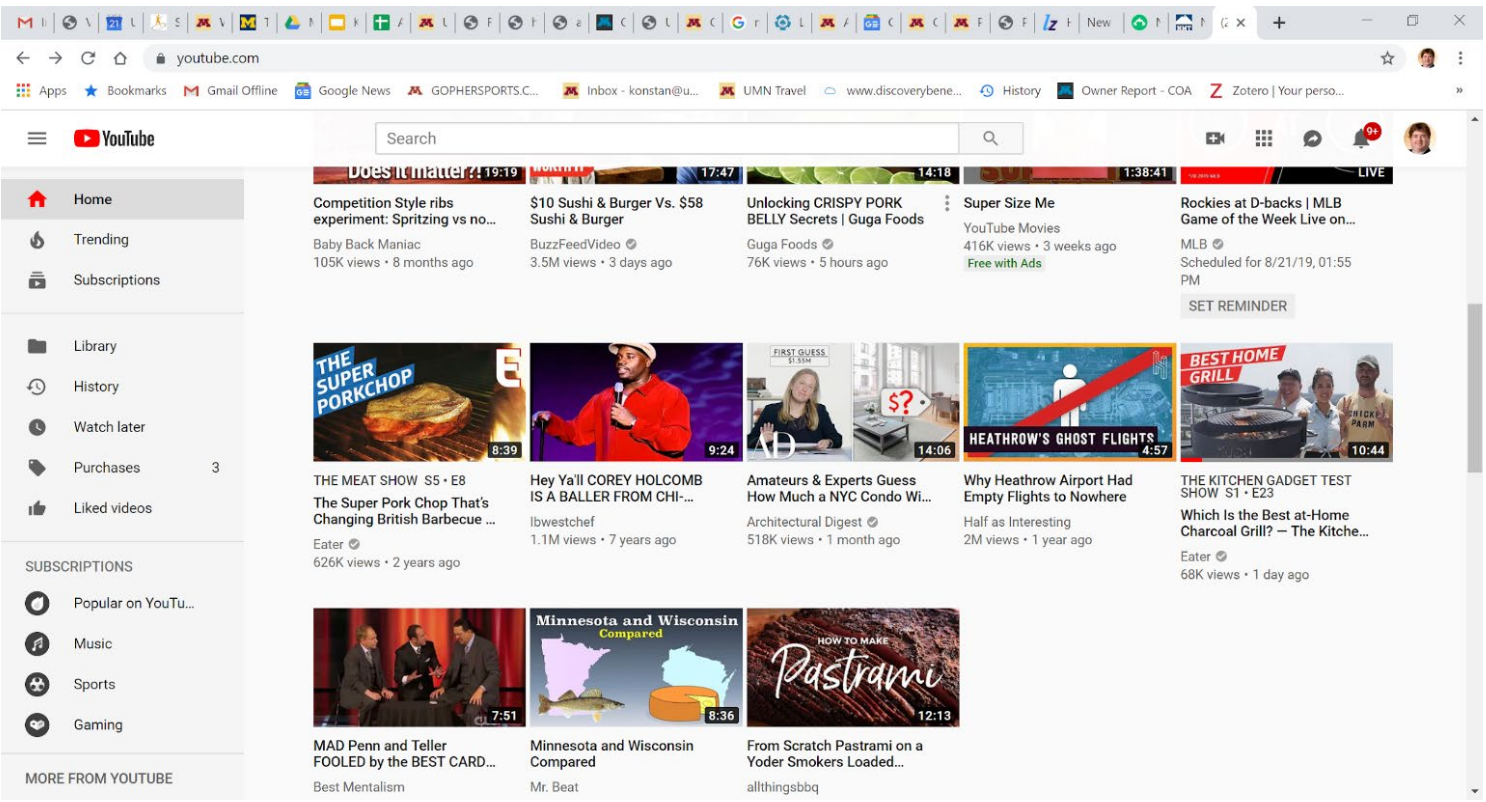

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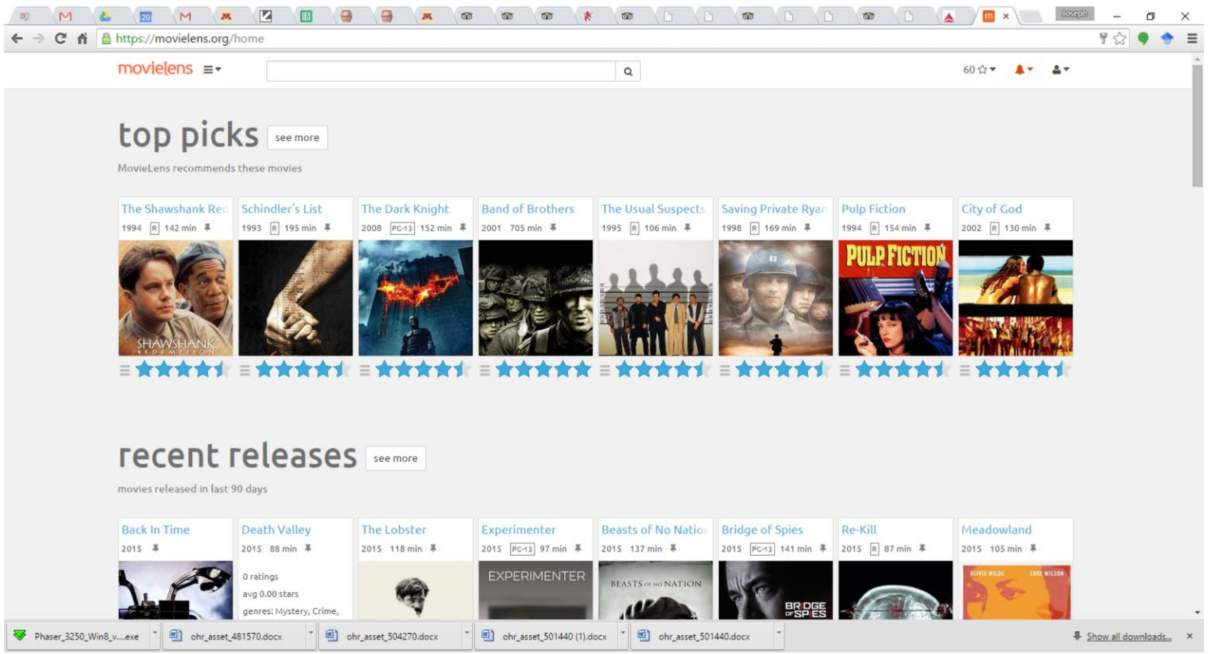

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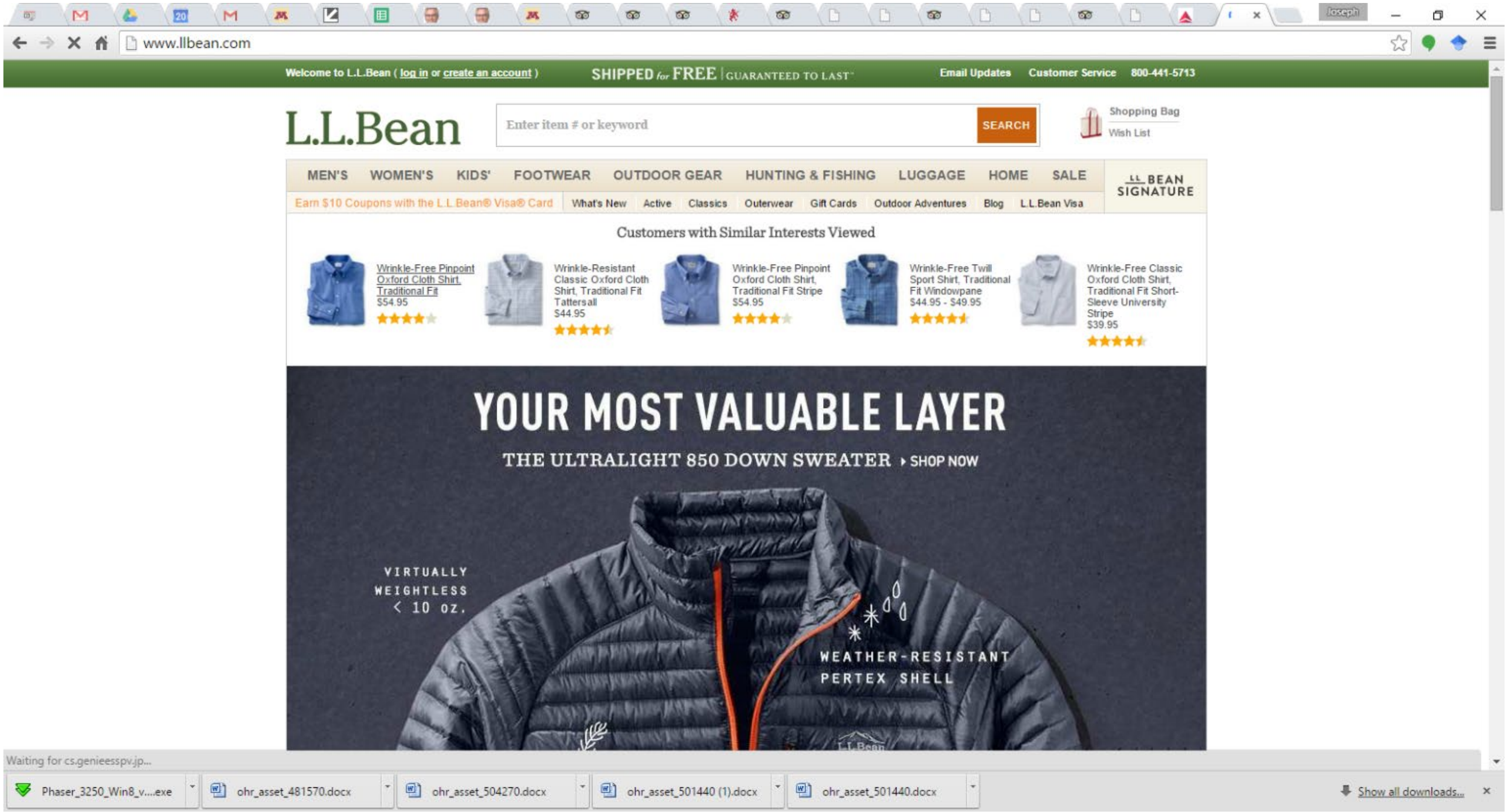


# What makes recommendations useful?

- Accuracy – likelihood of adoption
- Novelty – not something they would have found or adopted anyway
- Diversity – not all recommended the same
- Personalization – feeling that recommendation feels specific to recipient
- Explainability – can fit a story to the recommendation
- Business value – don't recommend what you don't want to offer/sell

# A Bit of RecSys Metrics History

» Researchers
- MAE, MSE, RMSE
- Correlation (rate/pred)
- Error Rates
- Retention Rates
- Top-k Metrics
- Survey Preferences

- *Most of all: statistically-significant improvements!*

» Businesses
- Click-through rate
- Conversion rate
- Lift

- Customer return and retention rates
- Time-on-site

- *Most of all: customer engagement, retention, and revenue*

# Some challenges in usefulness

- Diversity and Accuracy are trade-offs – this is a balancing act
- Novelty is not all good – customers need to be able to evaluate recommendations
- Personalization can also be a trade-off with accuracy – lots of people want the most popular stuff
- Explainability is hard – both technically and in terms customers can understand

# And Remember …

» Marketing is not a once-is-enough situation
  - A customer may need to see the recommendation many times before reacting to it (yet does not want to feel “nagged” about it).
  - The goal is usually not simply to sell the recommended item
    - Engage the customer in a deeper relationship
    - Lead to some form of sale, eventually

# The Metric Challenge

» Our Challenge:

- Translate user experience into something quantitative that others can optimize for …

- Two extremes (and lots of middle ground)
  - Theory-less experimentation
    – Optimize for sales in massive A/B tests
  - Theory-driven (and theory-building) exploration
    – Use, validate, and develop theories of user behavior

# Example:  Towards Useful

- Pause here for a brief rant on the difference between data mining and recommendation!

# Example: Towards Useful

- Pause here for a brief rant on the difference between data mining and recommendation!
  - Thanks! I feel better now
- Looking at Diversity and Serendipity
  - Even the definitions are hard:
    *Diversity*: How different recommendations are from each other?
    *Serendipity*: How unexpected recommendations are?

# Diversity and Serendipity

Cai-Nicolas Ziegler, Sean M. McNee, Joseph A. Konstan, and Georg Lausen. 2005. Improving recommendation lists through topic diversification. *Proc. WWW '05*.
Komal Kapoor, Vikas Kumar, Loren Terveen, Joseph A. Konstan, and Paul Schrater. 2015. "I like to explore sometimes": Adapting to Dynamic User Novelty Preferences. *Proc. RecSys '15*.

- Early work: confirmed intuition that diversification can add value *even when decreasing accuracy*
- Recent work by Kapoor/Kumar shows temporal changes in novelty-seeking among users

# Giving Users Control …

F. Maxwell Harper, Funing Xu, Harmanpreet Kaur, Kyle Condiff, Shuo Chang, and Loren Terveen. 2015. Putting Users in Control of their Recommendations. *Proc. RecSys '15*.
Michael D. Ekstrand, Daniel Kluver, F. Maxwell Harper, and Joseph A. Konstan. 2015. Letting Users Choose Recommender Algorithms: An Experimental Study. *Proc. RecSys '15*.

- We've started giving users greater control over their recommendation algorithms ….

# But Anchored in Understanding How User's See Recommendations

Michael D. Ekstrand, F. Maxwell Harper, Martijn C. Willemsen, and Joseph A. Konstan. 2014. User perception of differences in recommender algorithms. In *Proc. RecSys '14*.

» Virtual lab experiment to explore user perception of recommendations, varying algorithms and comparing perceptions with analytic metrics
  - Found that users overall prefer less novelty but more diversity.

# Next Steps:  Psych + Temporal

- Raghav Karumur carried out studies on links between Big-5 personality and user activity (UMAP 2016) and content preferences (RecSys 2016).

- Komal Kapoor and Vikas Kumar examined temporal changes in novelty preferences in music listening (RecSys 2015)

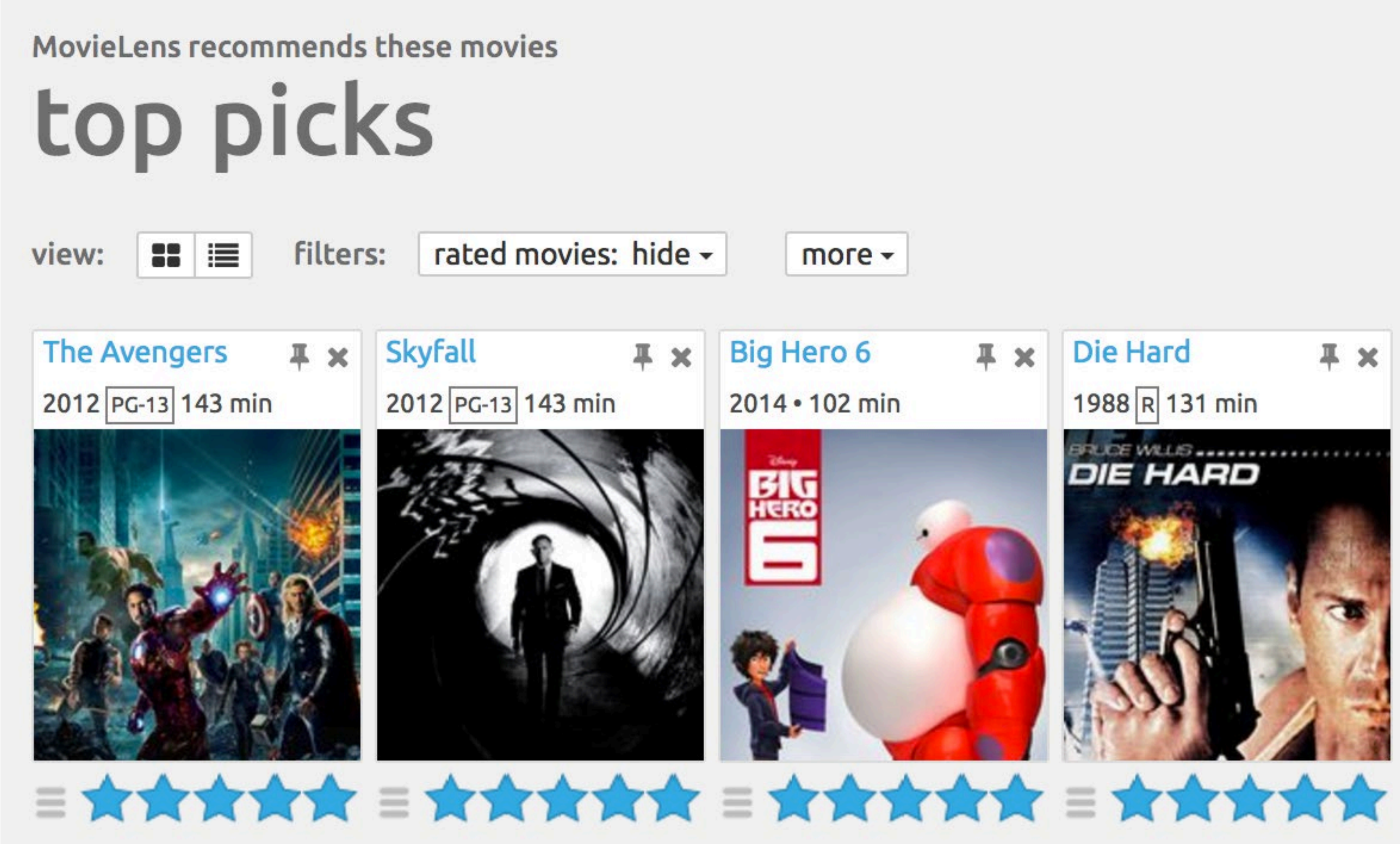
# Example: Re-Thinking Top-n

Qian Zhao, Gedaminas Adomavicius, F. Maxwell Harper, Martijn Willemsen, and Joseph A. Konstan. 2017. Toward Better Interactions in Recommender Systems: Cycling and Serpentining Approaches for Top-N Item Lists. *Proc CSCW '17*.

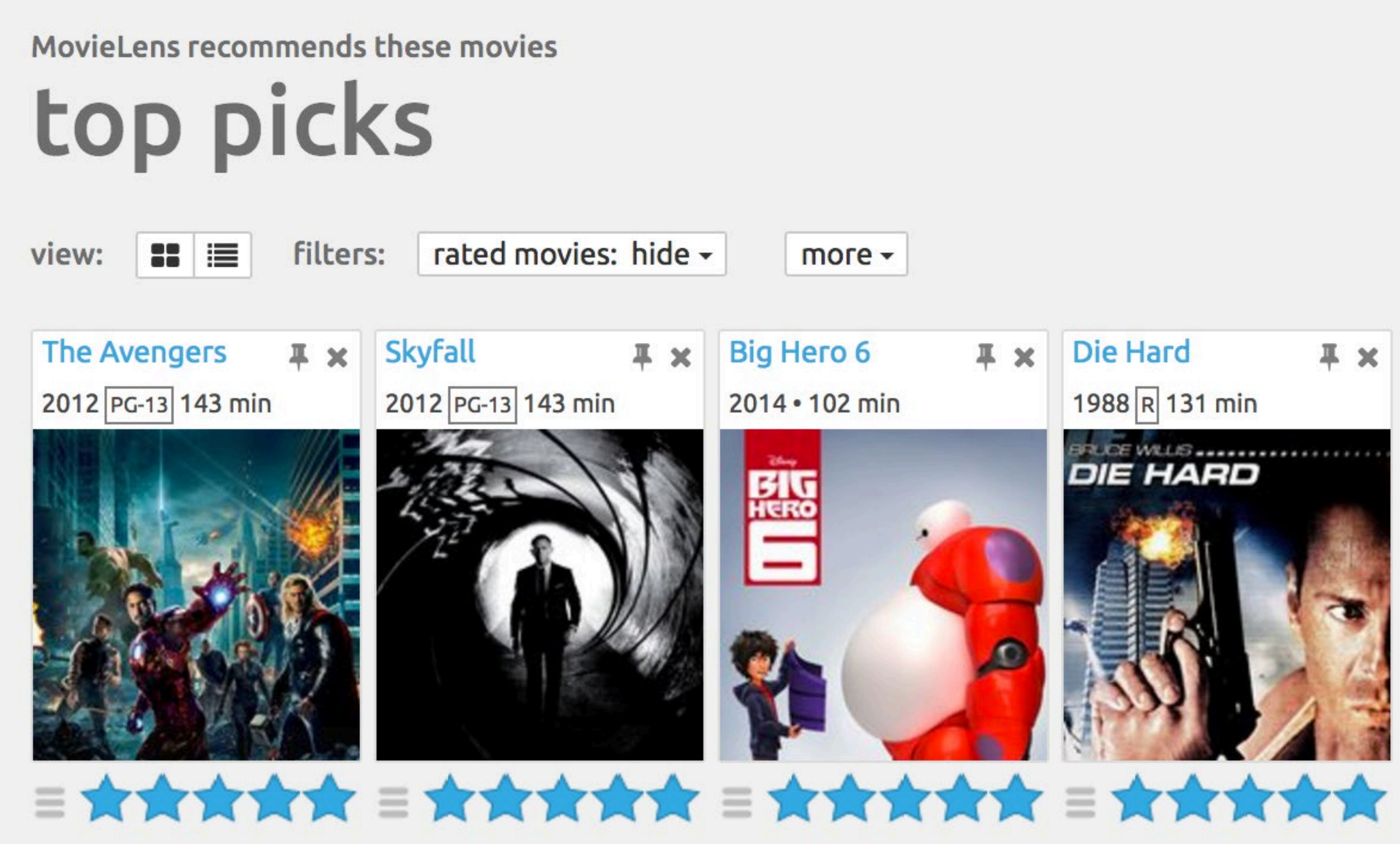
» Challenge two assumptions of top-n recommendation lists:

- That we should always start at the top
- That we should go in order from top to bottom

# 1st Visit


MovieLens recommends these movies
top picks
view:
filters:
rated movies: hide
more
The Avengers
2012 PG-13 143 min
Skyfall
2012 PG-13 143 min
Big Hero 6
2014 • 102 min
BIG HERO 6
Die Hard
1988 R 131 min
DIE HARD

# 2nd Visit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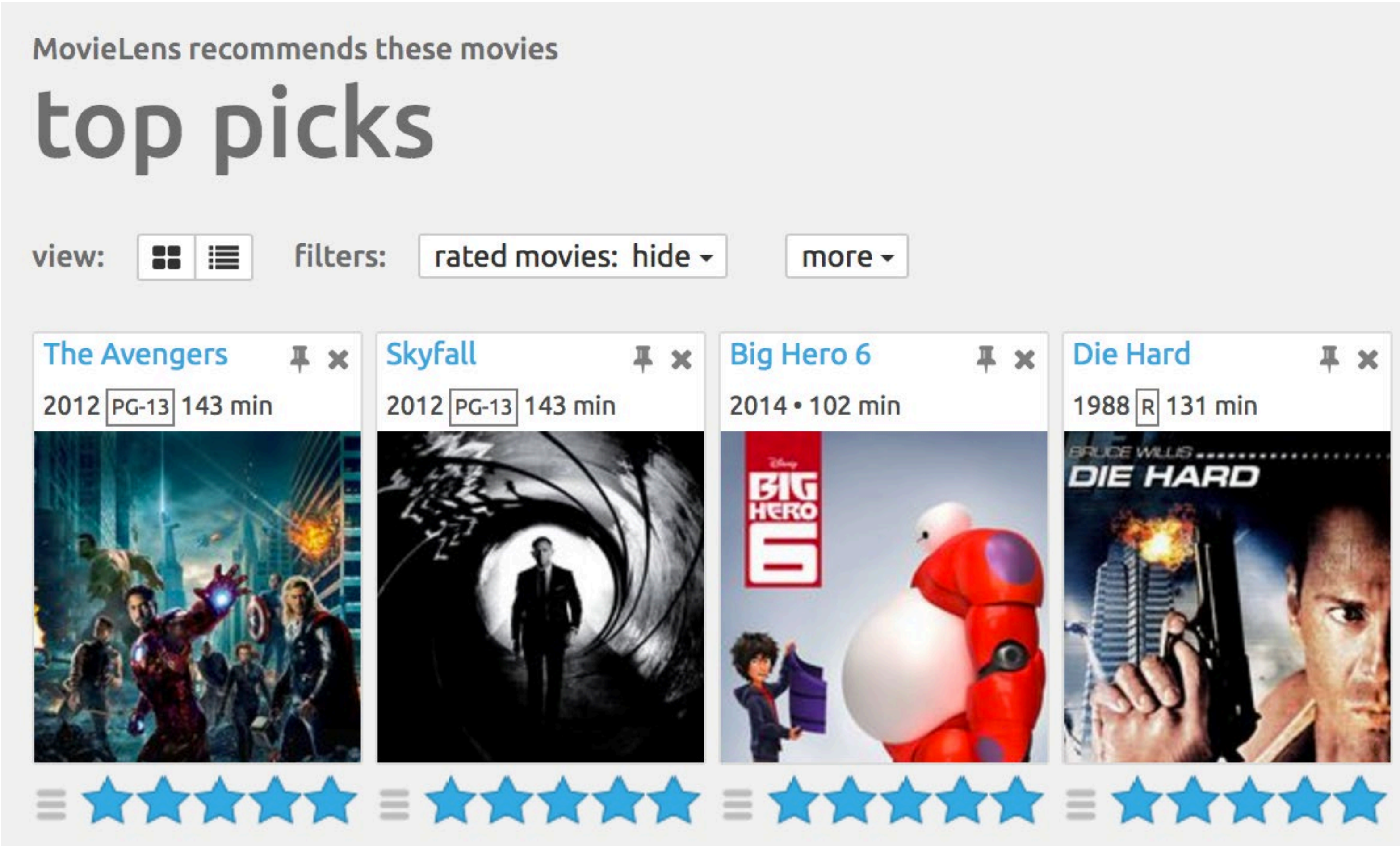
BRUCE WILLIS
DIE HARD

# 3rd ... Visit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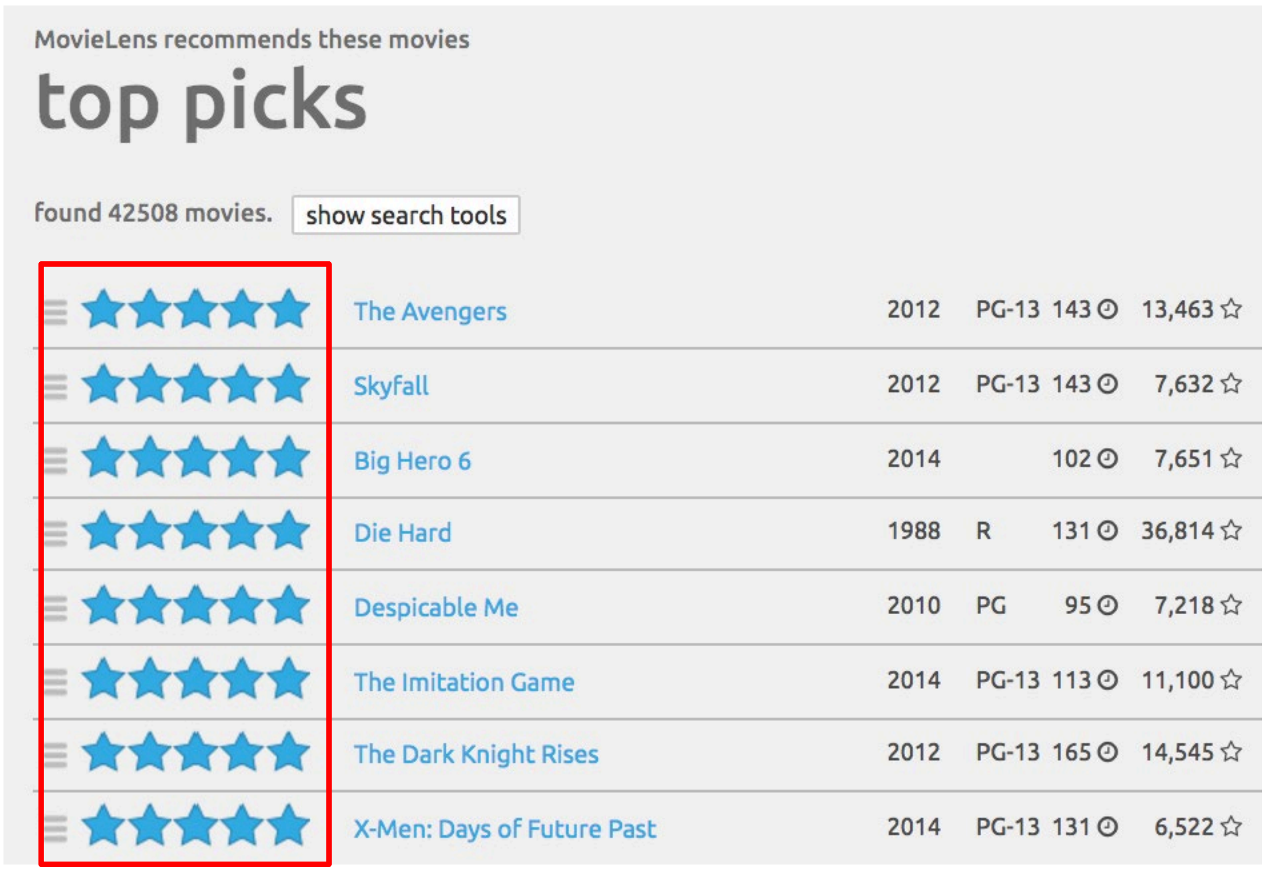
DIE HARD

Further exploration

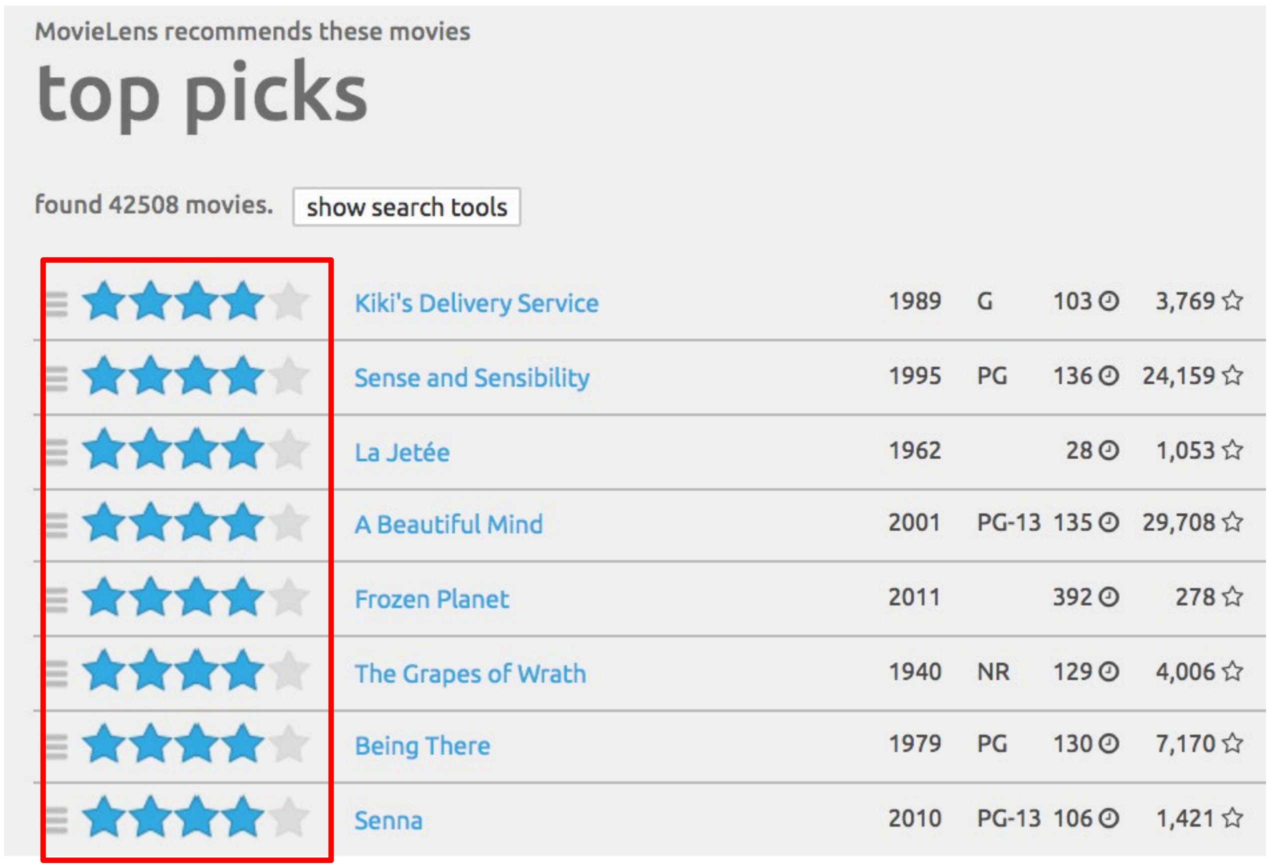
$\boxed{\downarrow}$

worse quality/experience

# 1st Page


MovieLens recommends these movies
top picks
found 42508 movies.
show search tools
The Avengers 2012 PG-13 143 13,463
Skyfall 2012 PG-13 143 7,632
Big Hero 6 2014 102 7,651
Die Hard 1988 R 131 36,814
Despicable Me 2010 PG 95 7,218
The Imitation Game 2014 PG-13 113 11,100
The Dark Knight Rises 2012 PG-13 165 14,545
X-Men: Days of Future Past 2014 PG-13 131 6,522

# 5th Page



MovieLens recommends these movies

top picks

found 42508 movies. show search tools

| | | | | |
|---|---|---|---|---|
| Kiki's Delivery Service | 1989 | G | 103 | 3,769 |
| Sense and Sensibility | 1995 | PG | 136 | 24,159 |
| La Jetée | 1962 | | 28 | 1,053 |
| A Beautiful Mind | 2001 | PG-13 | 135 | 29,708 |
| Frozen Planet | 2011 | | 392 | 278 |
| The Grapes of Wrath | 1940 | NR | 129 | 4,006 |
| Being There | 1979 | PG | 130 | 7,170 |
| Senna | 2010 | PG-13 | 106 | 1,421 |

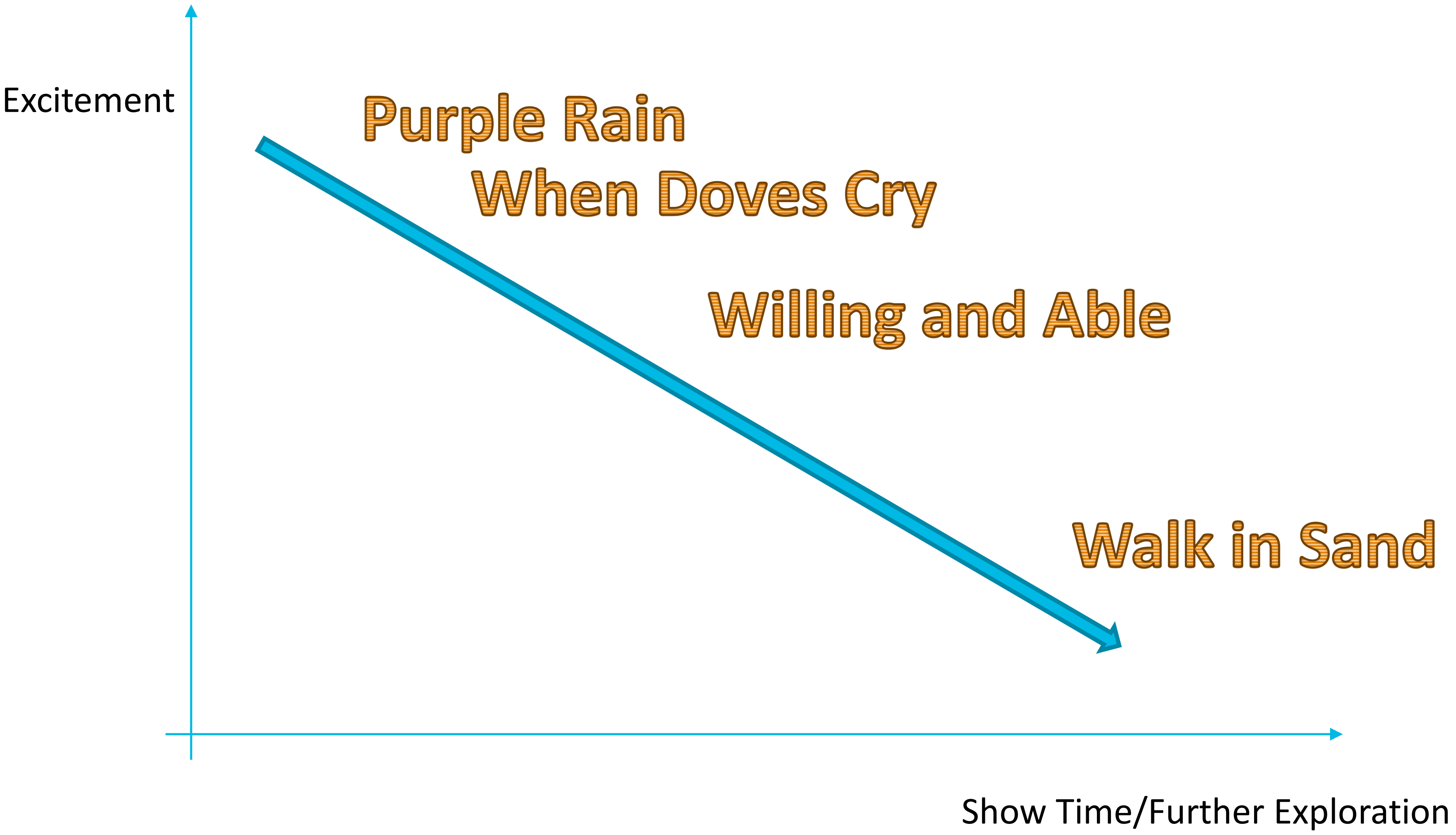
# $10^{th}$ … Page

MovieLens recommends these movies

## top picks

found 1087 movies. show search tools

| | | | | |
|---|---|---|---|---|
| The Mummy: Tomb of the Dragon Emperor | 2008 | PG-13 | 112 | 1,278 |
| A Good Day to Die Hard | 2013 | R | 98 | 857 |
| G.I. Joe: Retaliation | 2013 | PG-13 | 110 | 702 |
| Rambo: First Blood Part II | 1985 | R | 96 | 5,773 |
| Snakes on a Plane | 2006 | R | 105 | 2,266 |
| Teenage Mutant Ninja Turtles | 2014 | PG-13 | 101 | 725 |
| Abraham Lincoln: Vampire Hunter | 2012 | R | 94 | 836 |
| The Tuxedo | 2002 | PG-13 | 98 | 2,057 |


Excitement
Purple Rain
When Doves Cry
Willing and Able
Walk in Sand
Show Time/Further Exploration

# Experimenting with: Cycling and Serpentining

» ***Cycling*** demotes items that have been viewed several *(3+)* times, exposing fresher recommendations.

» ***Serpentining*** spreads top recommended items across several pages, offering high-quality items on each page as a user continues to explore.

# Cycling

| Movie | Score |
|---|---|
| **M1** | 5.0 |
| **M2** | 4.9 |
| **M3** | 4.6 |
| **M4** | 4.0 |

| Movie | Score | #display |
|---|---|---|
| | | |
| | | |
| **M1** | 5.0 | **3** |
| **M2** | 4.9 | **3** |

# Cycling

| Movie | Score |
|---|---|
| **M1** | 5.0 |
| **M2** | 4.9 |
| **M3** | 4.6 |
| **M4** | 4.0 |

| Movie | Score | #display |
|---|---|---|
| **M3** | 4.6 | 0 |
| **M4** | 4.0 | 0 |
| **M1** | 5.0 | 3 |
| **M2** | 4.9 | 3 |

# Serpentining

p. 1

p. 2

| Movie | Score |
|---|---|
| M1 | 5.0 |
| M2 | 4.9 |
| M3 | 4.8 |
| M4 | 4.7 |
| M5 | 4.6 |
| M6 | 4.5 |
| M7 | 4.4 |
| M8 | 4.3 |

| Movie | Score |
|---|---|
| M1 | 5.0 |
| M3 | 4.8 |
| M5 | 4.6 |
| M7 | 4.4 |
| | |
| | |
| | |
| | |

p. 1

p. 2

# Serpentining

p. 1

p. 2

| Movie | Score |
|---|---|
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| M3 | 4.8 |
| M4 | 4.7 |
| M5 | 4.6 |
| M6 | 4.5 |
| M7 | 4.4 |
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| Movie | Score |
|---|---|
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| M3 | 4.8 |
| M5 | 4.6 |
| M7 | 4.4 |
| M2 | 4.9 |
| M4 | 4.7 |
| M6 | 4.5 |
| M8 | 4.3 |

p. 1

p. 2

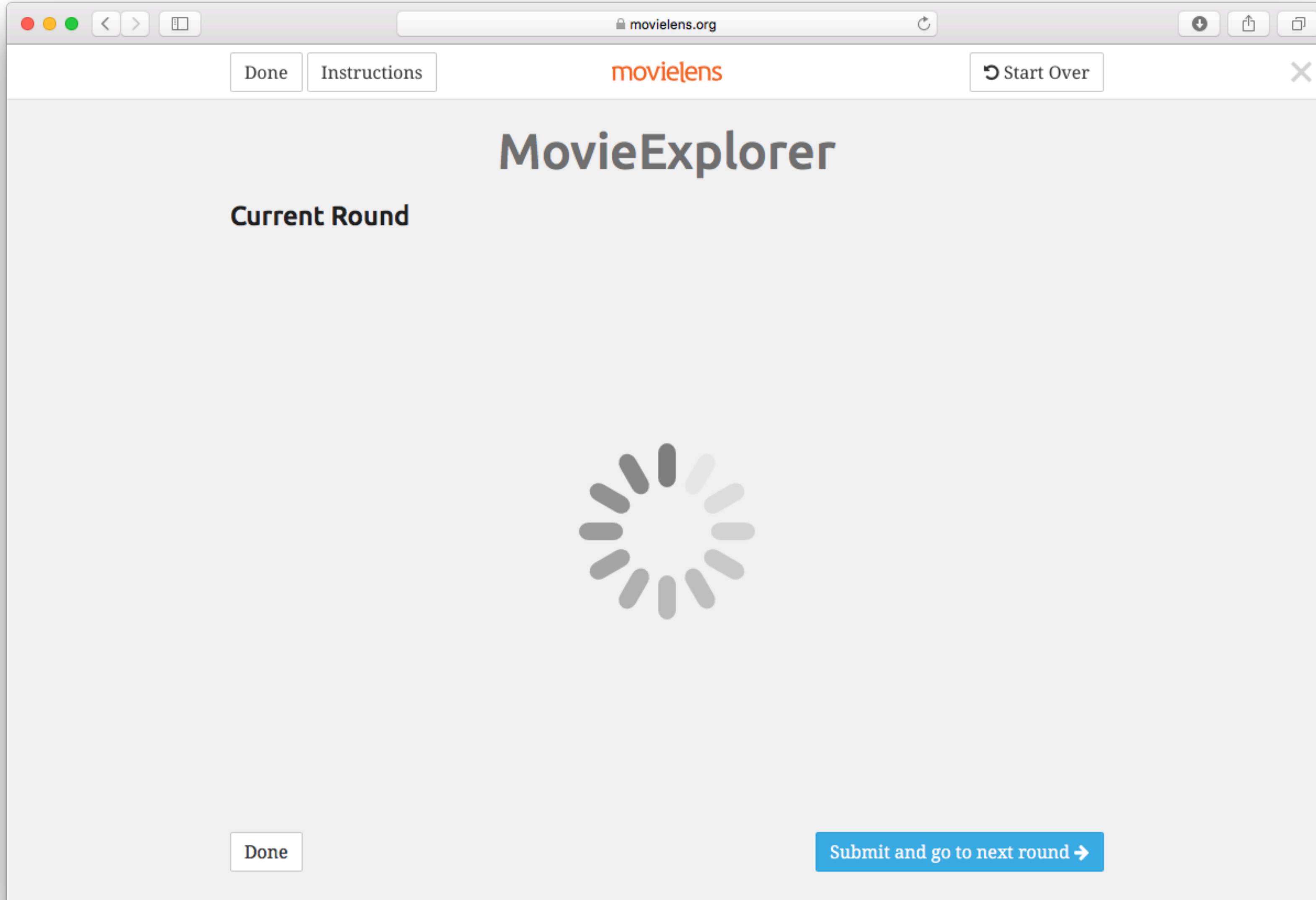
| | No Cycling | Within-session Cycling | Between-session Cycling |
|---|---|---|---|
| **No Serpentining** | **control condition** | *opt out rate: +*<br>*#page views: +*<br>*#interested: +*<br>*interested rate: +*<br><br>accuracy: -<br>familiarity: -<br>usefulness: -<br>change: +<br>freshness: + | *#page views: +*<br>*#interested: +*<br><br>accuracy: -<br>confusion: +<br>change: + |
| **Serpentining** | *#page views: +*<br>*#interested: +*<br><br>accuracy: -<br>familiarity: -<br>usefulness: - | **too complicated manipulation**<br>**no interesting sig. results**<br><br>**see the paper for details** | |

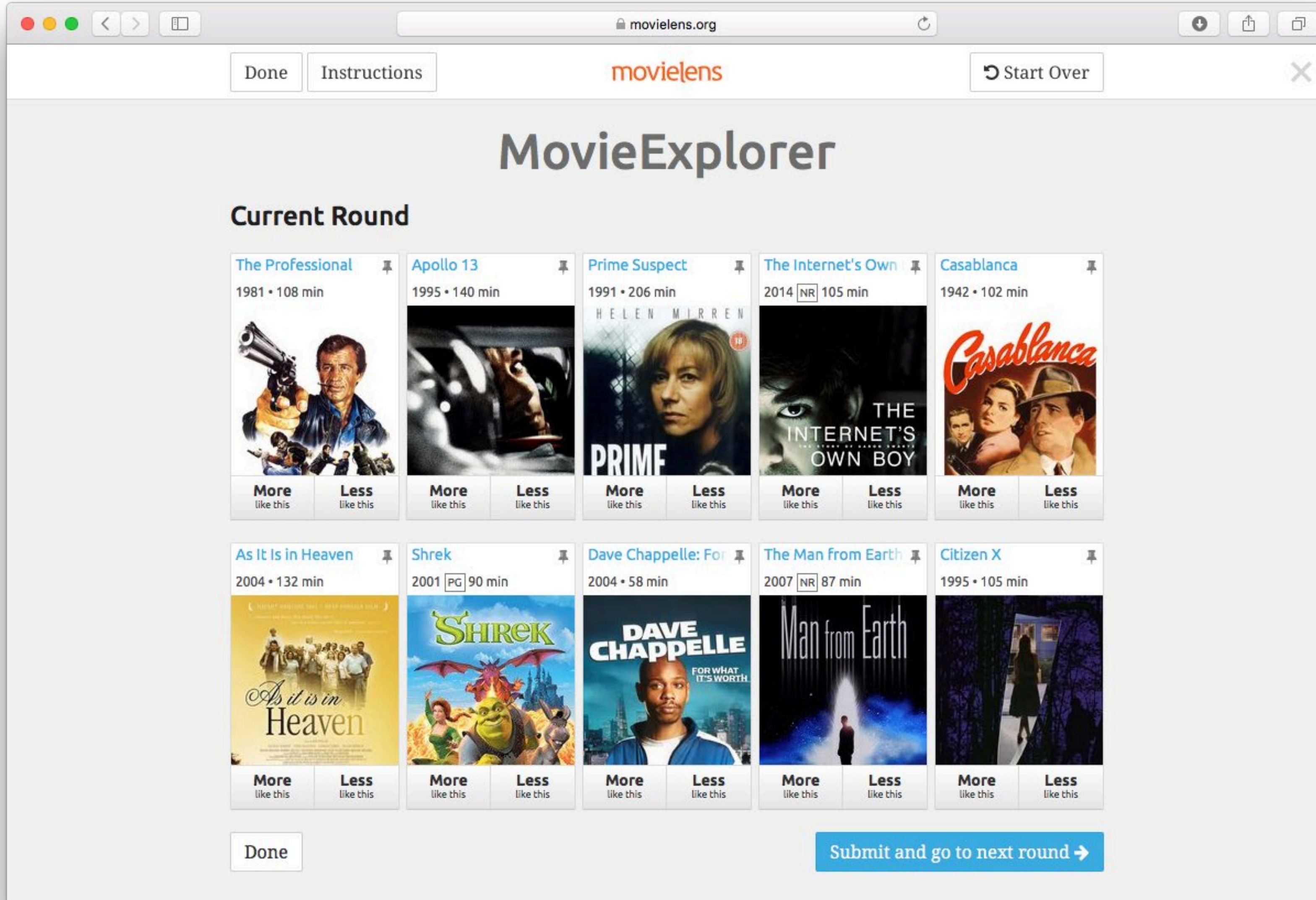
Only significant results are shown.
Italic: objective metrics; Non-italic: subjective metrics

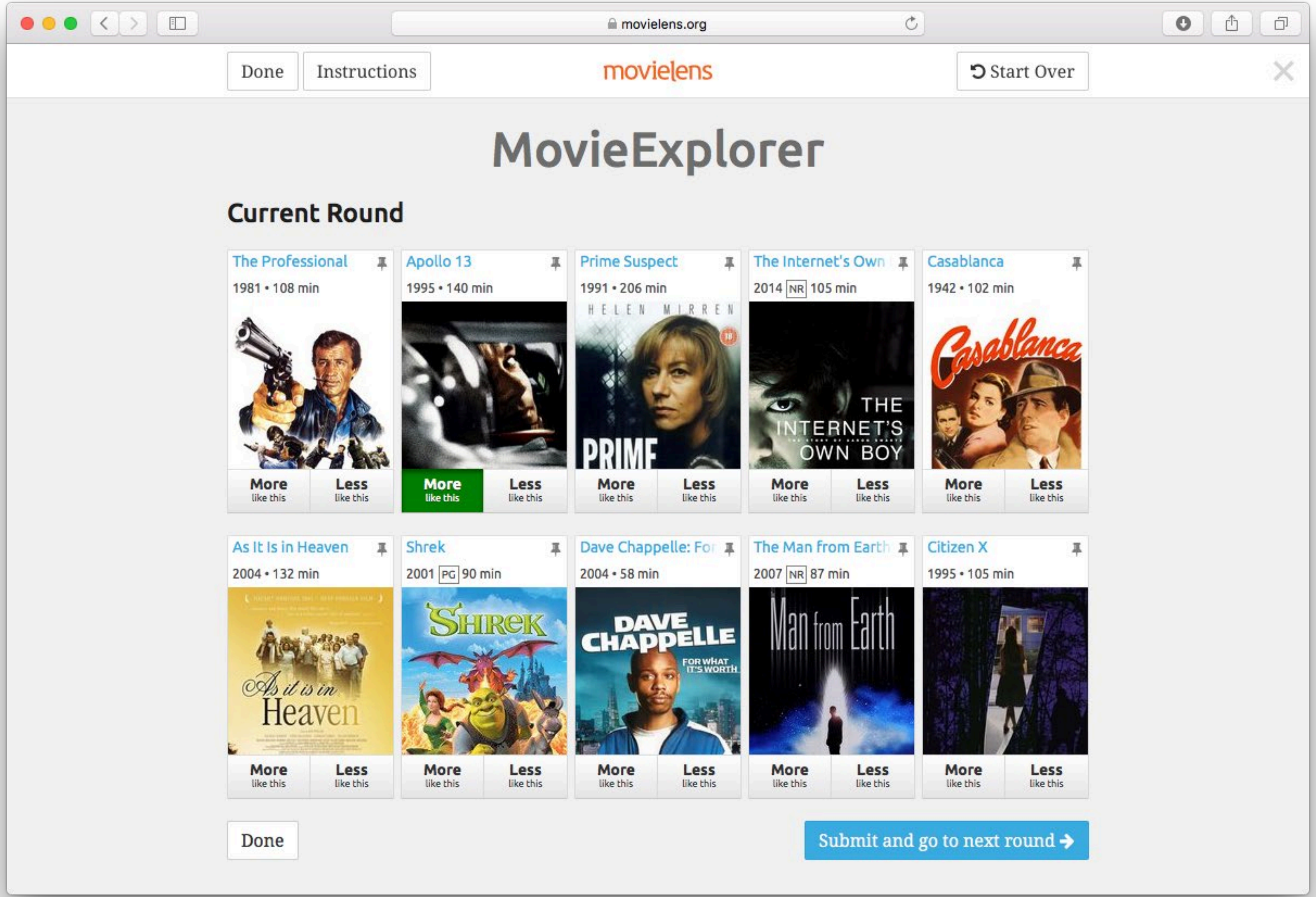
# Example:  Exploration

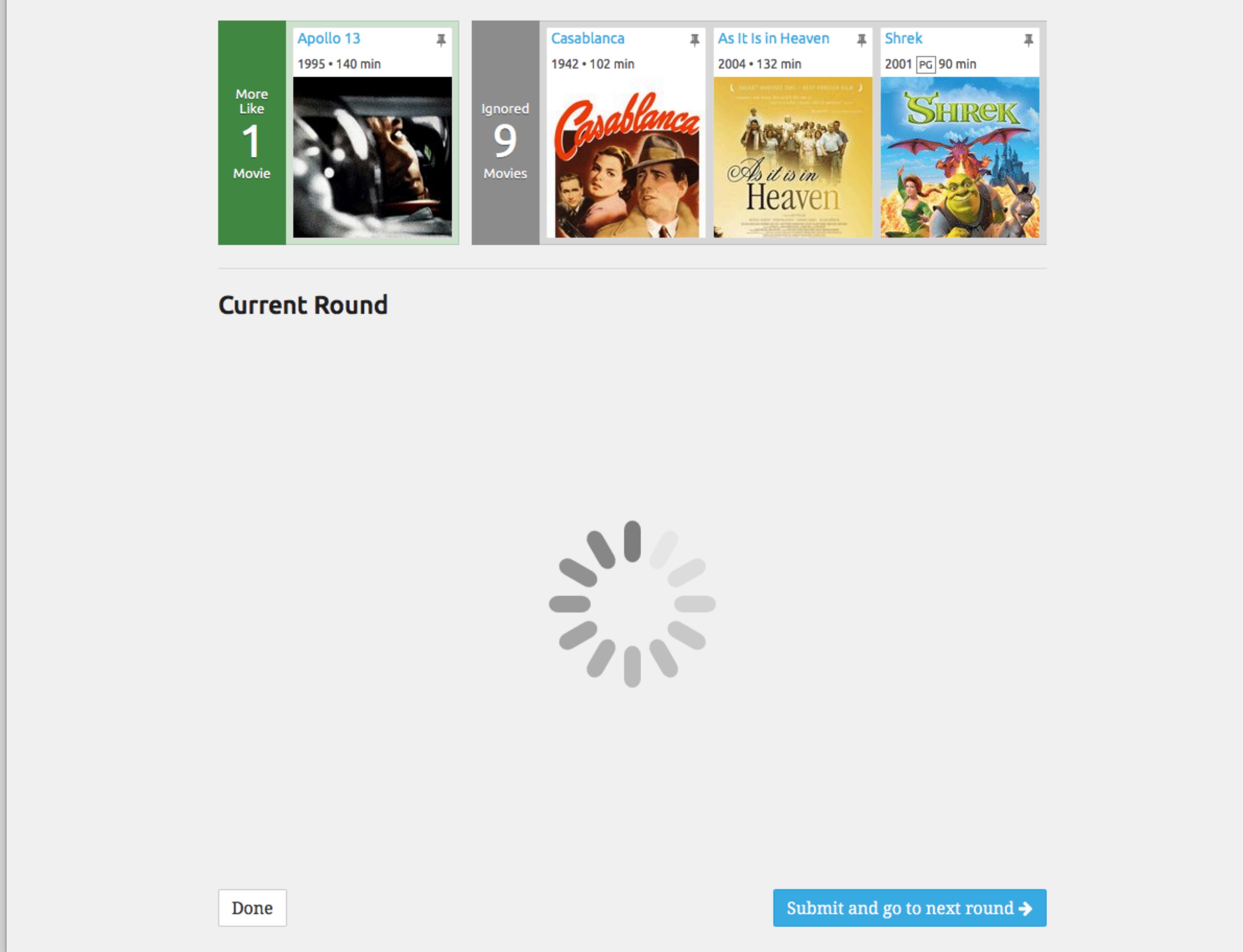
Taavi Taijala, Martijn C. Willemsen, and Joseph A. Konstan.  MovieExplorer: Building an Interactive Exploration Tool from Ratings and Latent Taste Spaces. *Proc. ACM SAC 2018 pp. 1383-1392.*

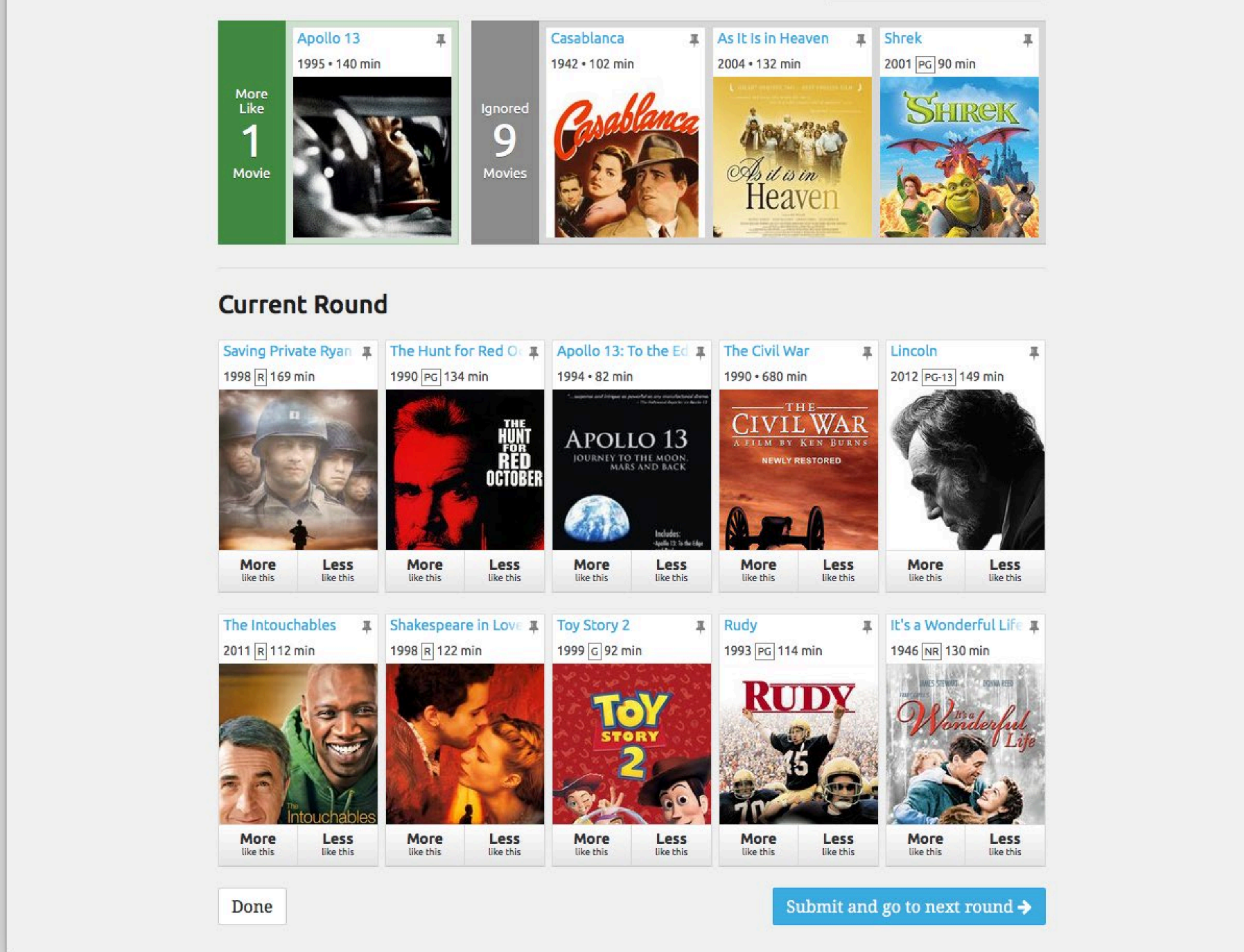
» Can we better serve users by *not recommending* but rather letting them *explore?*
  - How?
  - For what tasks?

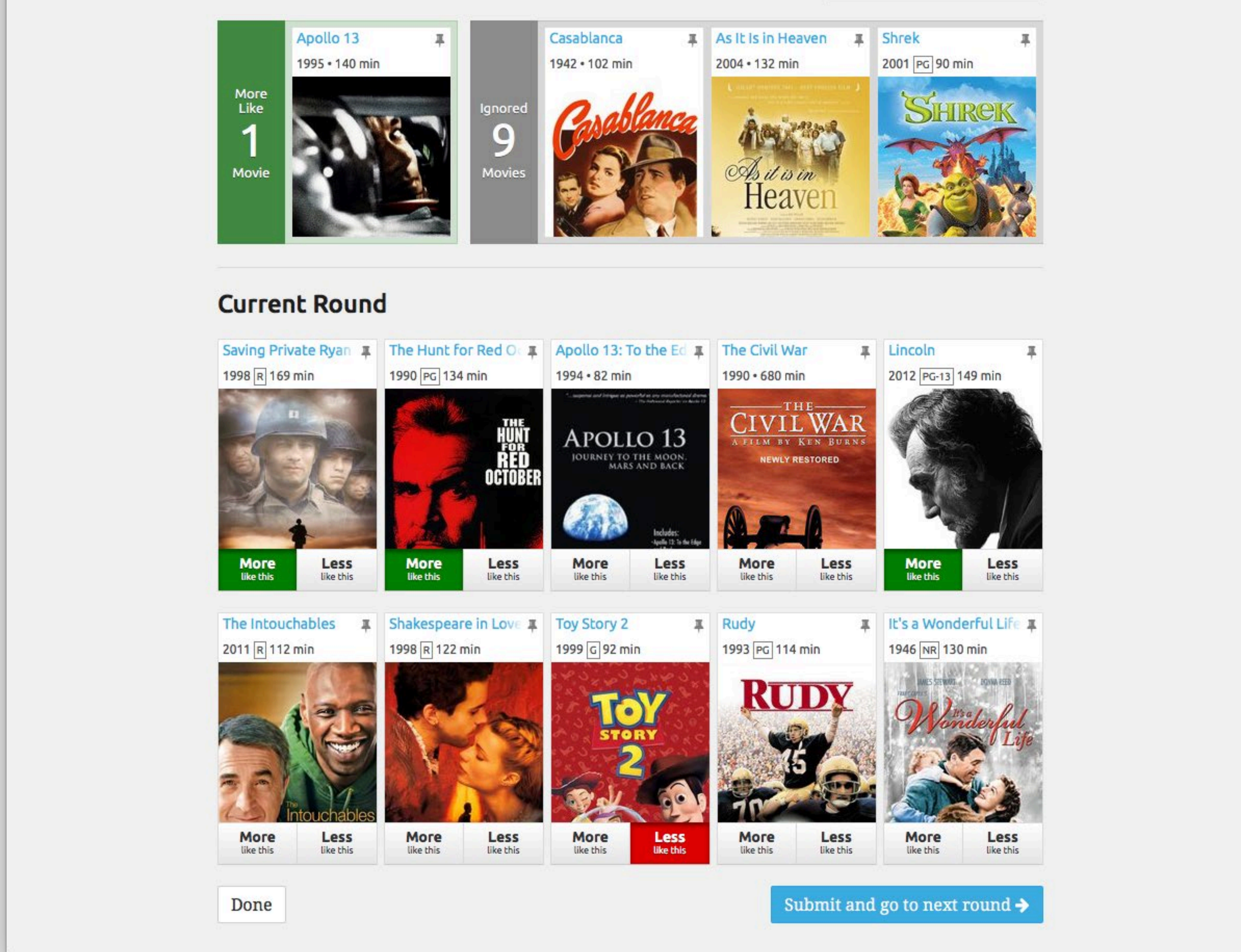

movielens.org
Done
Instructions
movielens
Start Over
MovieExplorer
Current Round
Done
Submit and go to next round

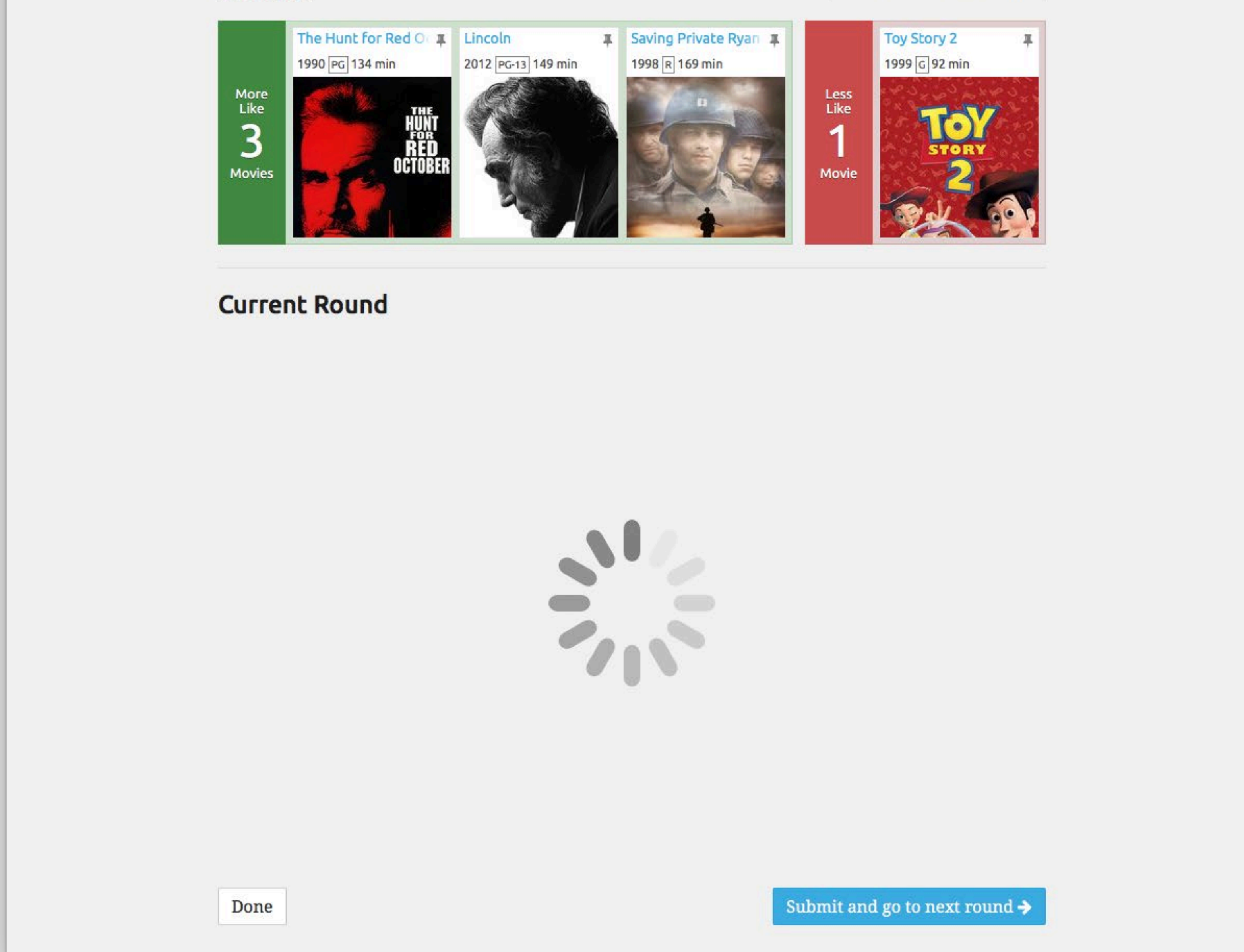

movielens.org
Done
Instructions
movielens
Start Over
MovieExplorer
Current Round
The Professional
1981 • 108 min
Apollo 13
1995 • 140 min
Prime Suspect
1991 • 206 min
The Internet's Own
2014 NR 105 min
Casablanca
1942 • 102 min
As It Is in Heaven
2004 • 132 min
Shrek
2001 PG 90 min
Dave Chappelle: For
2004 • 58 min
The Man from Earth
2007 NR 87 min
Citizen X
1995 • 105 min
More like this
Less like this
Done
Submit and go to next round

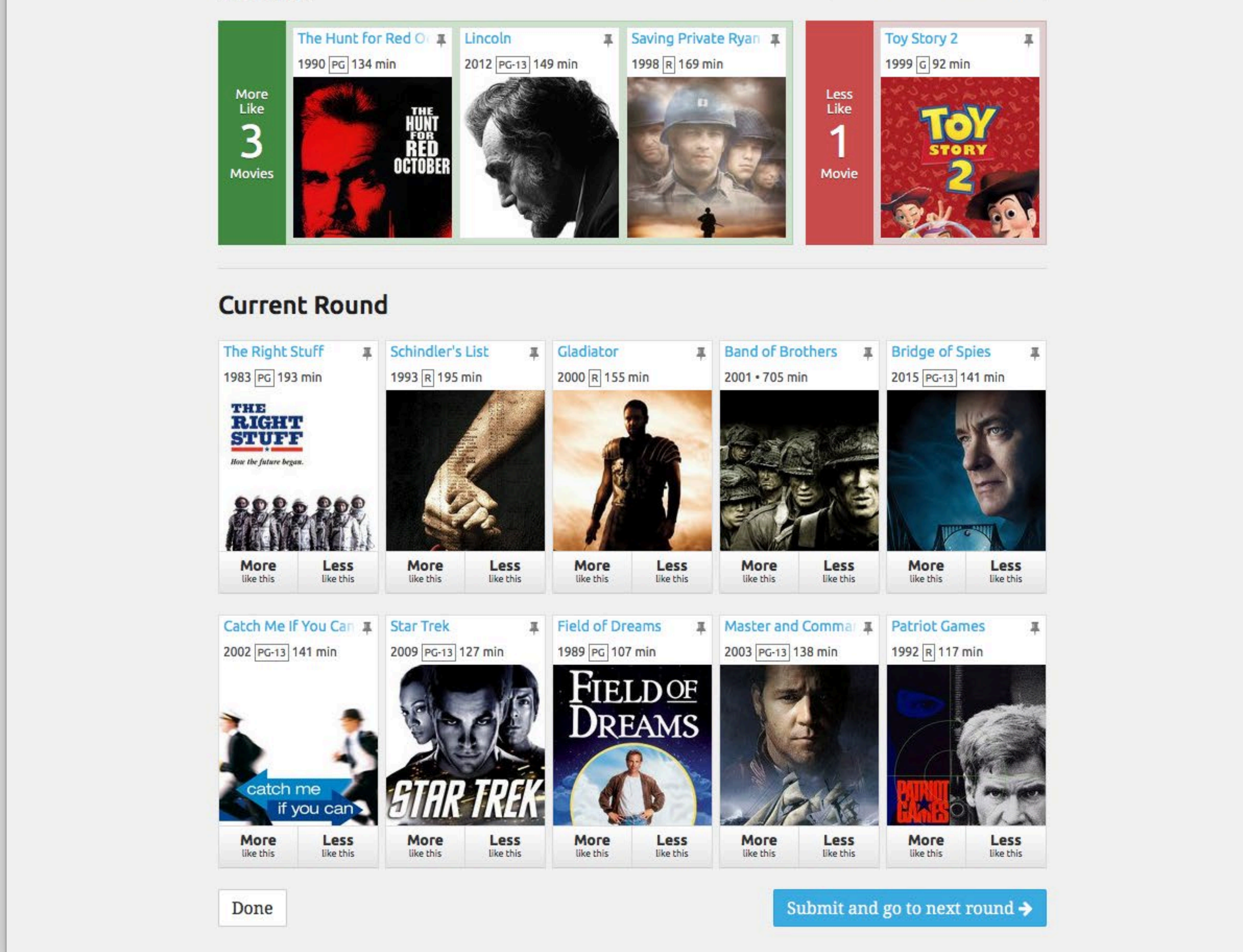

movielens.org
Done
Instructions
movielens
Start Over
MovieExplorer
Current Round
The Professional
1981 • 108 min
Apollo 13
1995 • 140 min
Prime Suspect
1991 • 206 min
The Internet's Own
2014 NR 105 min
Casablanca
1942 • 102 min
More like this
Less like this
As It Is in Heaven
2004 • 132 min
Shrek
2001 PG 90 min
Dave Chappelle: For
2004 • 58 min
The Man from Earth
2007 NR 87 min
Citizen X
1995 • 105 min
More like this
Less like this
Done
Submit and go to next round

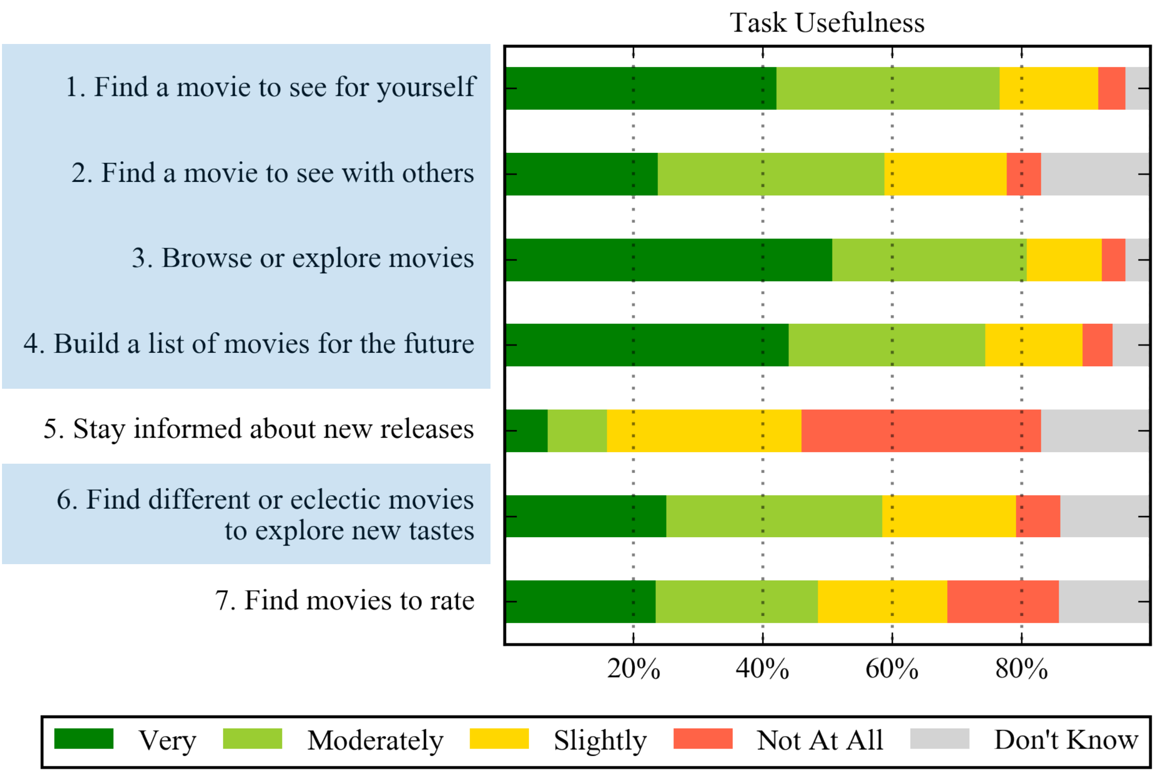

More Like
1
Movie
Apollo 13
1995 • 140 min
Ignored
9
Movies
Casablanca
1942 • 102 min
As It Is in Heaven
2004 • 132 min
Shrek
2001 PG 90 min
Current Round
Done
Submit and go to next round

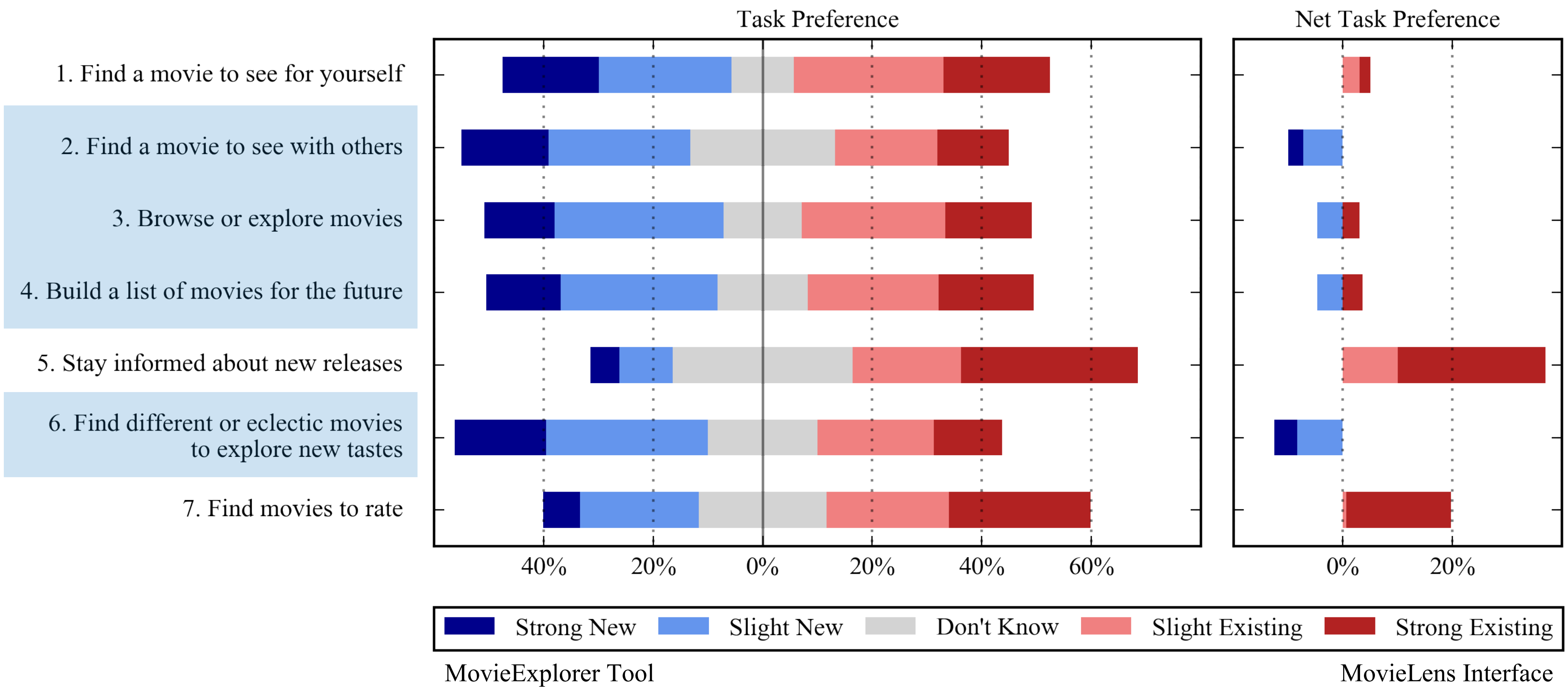

More Like
1
Movie
Apollo 13
1995 • 140 min
Ignored
9
Movies
Casablanca
1942 • 102 min
As It Is in Heaven
2004 • 132 min
Shrek
2001 PG 90 min
Current Round
Saving Private Ryan
1998 R 169 min
The Hunt for Red O
1990 PG 134 min
Apollo 13: To the Ed
1994 • 82 min
The Civil War
1990 • 680 min
Lincoln
2012 PG-13 149 min
The Intouchables
2011 R 112 min
Shakespeare in Love
1998 R 122 min
Toy Story 2
1999 G 92 min
Rudy
1993 PG 114 min
It's a Wonderful Life
1946 NR 130 min
More like this
Less like this
Done
Submit and go to next round


More Like
1
Movie
Apollo 13
1995 • 140 min
Ignored
9
Movies
Casablanca
1942 • 102 min
As It Is in Heaven
2004 • 132 min
Shrek
2001 PG 90 min
Current Round
Saving Private Ryan
1998 R 169 min
The Hunt for Red O
1990 PG 134 min
Apollo 13: To the Ed
1994 • 82 min
The Civil War
1990 • 680 min
Lincoln
2012 PG-13 149 min
The Intouchables
2011 R 112 min
Shakespeare in Love
1998 R 122 min
Toy Story 2
1999 G 92 min
Rudy
1993 PG 114 min
It's a Wonderful Life
1946 NR 130 min
More like this
Less like this
Done
Submit and go to next round


More Like
3
Movies
The Hunt for Red O
1990 PG 134 min
THE HUNT FOR RED OCTOBER
Lincoln
2012 PG-13 149 min
Saving Private Ryan
1998 R 169 min
Less Like
1
Movie
Toy Story 2
1999 G 92 min
TOY STORY 2
Current Round
Done
Submit and go to next round


More Like 3 Movies
The Hunt for Red O
1990 PG 134 min
THE HUNT FOR RED OCTOBER
Lincoln
2012 PG-13 149 min
Saving Private Ryan
1998 R 169 min
Less Like 1 Movie
Toy Story 2
1999 G 92 min
TOY STORY 2
Current Round
The Right Stuff
1983 PG 193 min
THE RIGHT STUFF
How the future began.
Schindler's List
1993 R 195 min
Gladiator
2000 R 155 min
Band of Brothers
2001 • 705 min
Bridge of Spies
2015 PG-13 141 min
Catch Me If You Can
2002 PG-13 141 min
catch me if you can
Star Trek
2009 PG-13 127 min
STAR TREK
Field of Dreams
1989 PG 107 min
FIELD OF DREAMS
Master and Comma
2003 PG-13 138 min
Patriot Games
1992 R 117 min
PATRIOT GAMES
More like this
Less like this
Done
Submit and go to next round


Task Usefulness
1. Find a movie to see for yourself
2. Find a movie to see with others
3. Browse or explore movies
4. Build a list of movies for the future
5. Stay informed about new releases
6. Find different or eclectic movies to explore new tastes
7. Find movies to rate
20%
40%
60%
80%
Very
Moderately
Slightly
Not At All
Don't Know


Task Preference
Net Task Preference
1. Find a movie to see for yourself
2. Find a movie to see with others
3. Browse or explore movies
4. Build a list of movies for the future
5. Stay informed about new releases
6. Find different or eclectic movies
to explore new tastes
7. Find movies to rate
40%
20%
0%
20%
40%
60%
0%
20%
Strong New
Slight New
Don't Know
Slight Existing
Strong Existing
MovieExplorer Tool
MovieLens Interface

# Why I Both Hate and Love Machine Learning

» Hate
- Too often solving the wrong problem, efficiently, and at scale!
- The easier it is to solve the wrong problem, the more we do it!

» Love
- When solving the right problem …
- Inherent appeal of having some natural, underlying structure
- Potential to build it whatever it is that we can measure

# Take-Away Messages

1. Recommender Systems are not missing data problems; they are challenges in being useful.
2. Algorithms don’t figure out the right problem to solve …
3. Need a bridge between human studies and efficient computation …
4. Metrics are one useful bridge …
5. Studies -> Metrics -> Algorithms

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konstan@umn.edu

# QUESTIONS

# The Learning Continues…

TechTalk Discourse Forum: https://on.acm.org

TechTalk Inquiries: learning@acm.org

Learning Center & TechTalk Archives: https://learning.acm.org

Professional Ethics: https://ethics.acm.org

Queue Magazine: https://queue.acm.org