# User preference dynamics

## You ain’t gonna wear Star Wars t-shirts forever...

Miroslav Rác, Mar 2019

# Users change their interests

- **time bias** - global change in community
- **user bias shifting** - users change their rating behavior, eg. becomes pickier
- **item bias shifting** - temporal popularity of times
- **natural change** of individual’s interest

# Time bias

At different ages, peoples enjoy different things

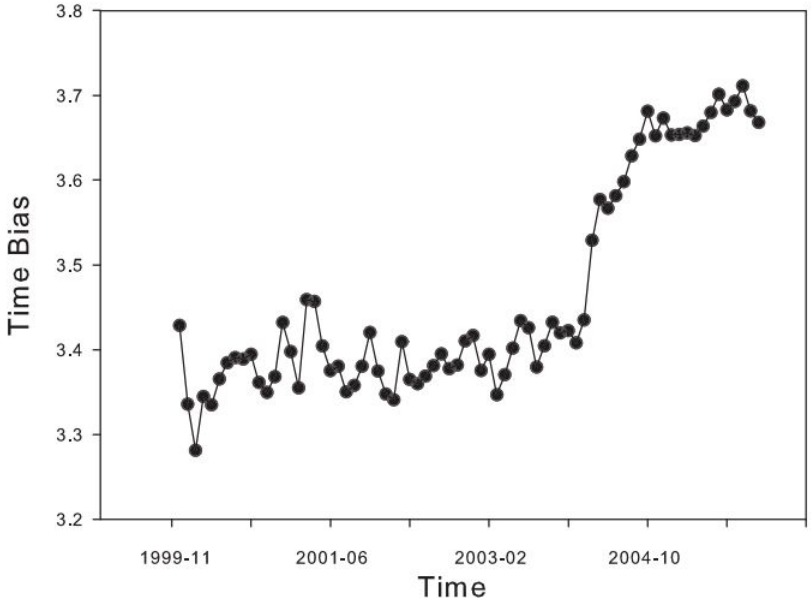



Figure 2. Distribution of $\bar{r}_t$ in Netflix data.

# User bias shifting

Users may change their rating habit with time.

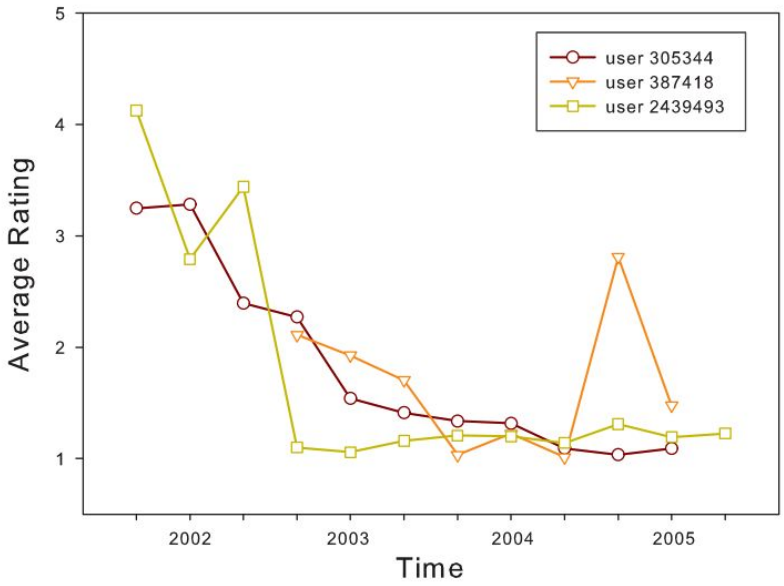



Figure 3. Distribution of $\bar{r}_{ut}$ in Netflix data.

# Item bias shifting

The popularity of items change with time.

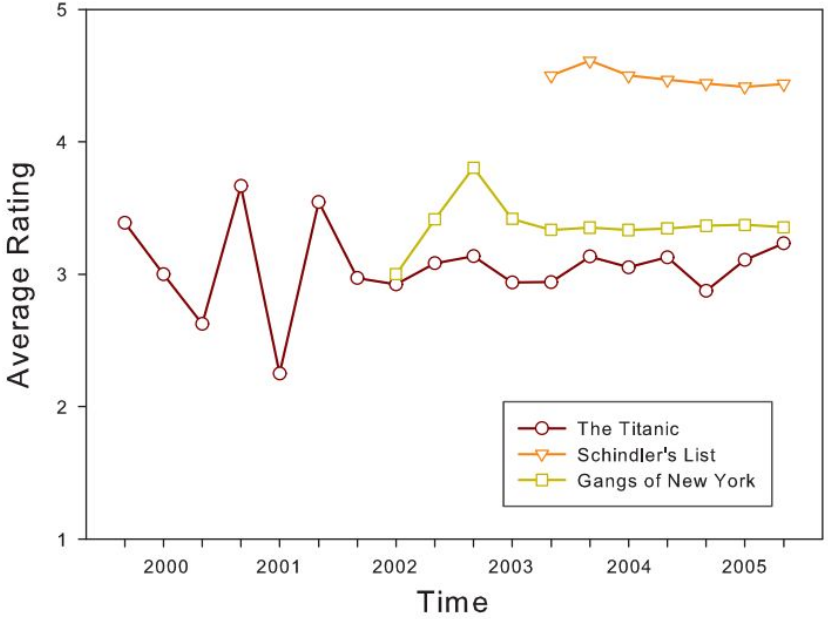



Figure 4. Distribution of $\bar{r}_{it}$ in Netflix data.

# Natural change in individual’s interest

young boy like fairy tail movies but enyojs war movies when grows up

May happen under influence of many external factors/invisible events.

# Concept drift

non-stationary learning problem

$$\exists X : p_{t_0}(X, y) \neq p_{t_1}(X, y),$$

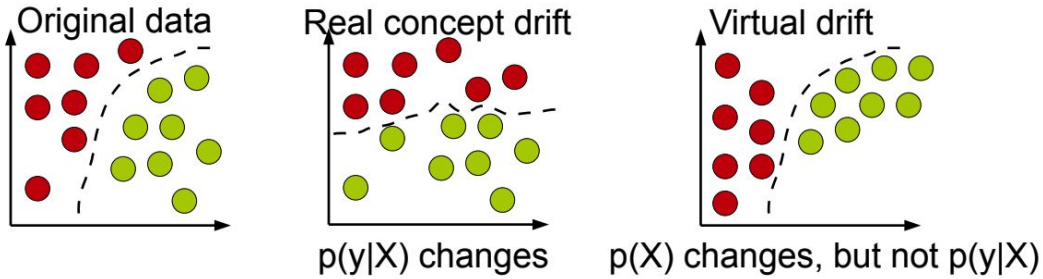
core assumption: uncertainty about the future

therefore, seasonality is **not** a concept drift

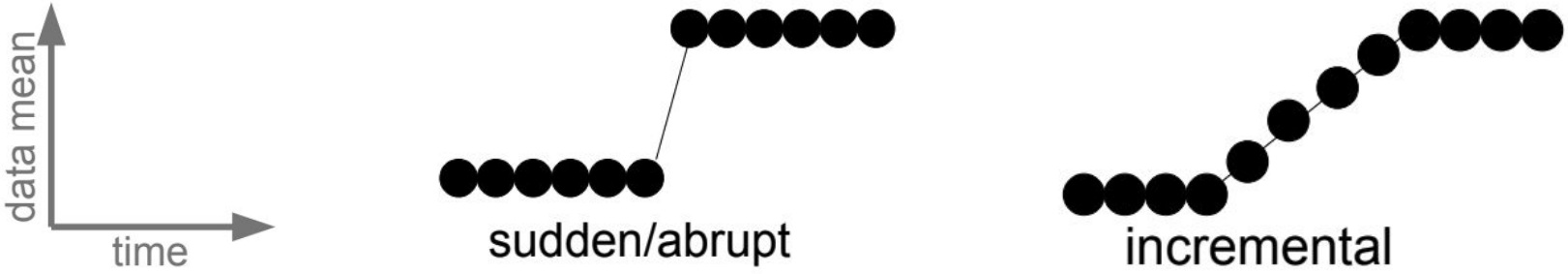
# Real and virtual concept drift

Real: change in p(y|X) with or without change in p(X)

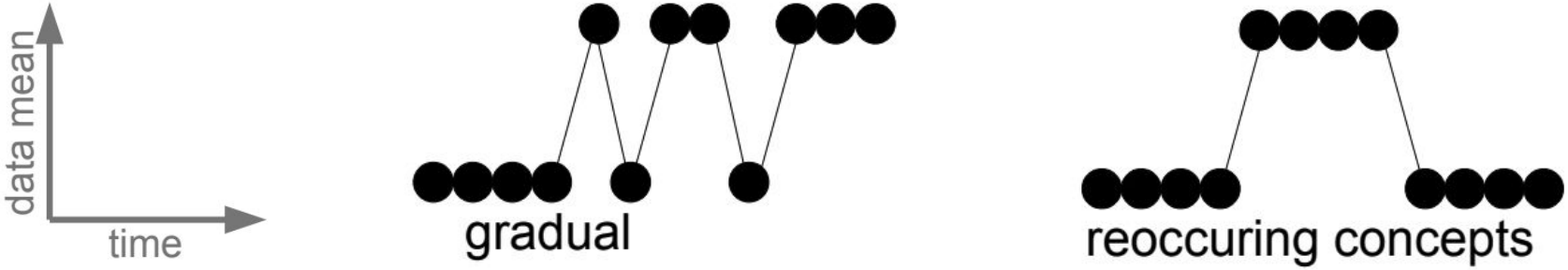
Virtual: change in data distribution p(X) without affecting p(y|X)



# Change types: sudden and incremental

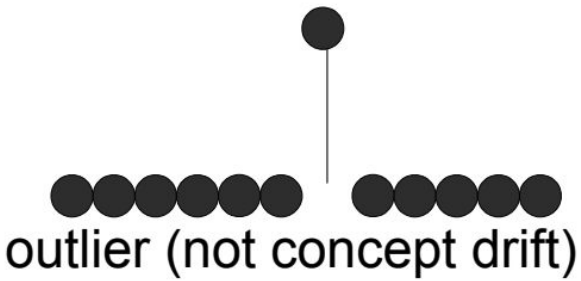


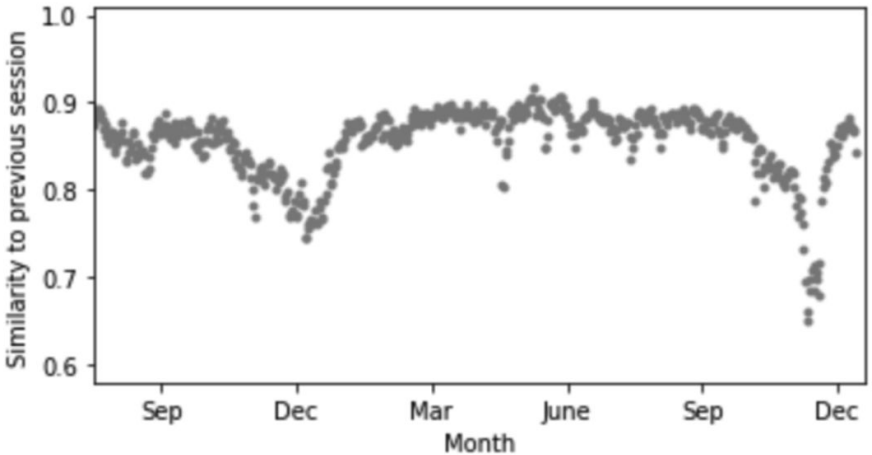
# Change types: gradual and reoccuring



# Noise is not a concept drift

challenge: distinguishing between true concept drift and noise



# Time-aware recommender systems

- Restricting training data to recent records
- Bayesian probabilistic tensor factorization, which enhances traditional collaborative filtering with temporal features. Therefore, it is able to learn latent features evolving in the time on the global basis.
- Split the observed data by predefined time periods. Users are modelled for every chunk separately. Using exponential smoothing technique to lower the importance and eventually eliminate older preferences.
- Introducing the UPD (User-Preference Dynamics) measure which captures the rate with which the current preferences of each user have been shifted Metric value is maintained for each user and it is used to weight importance of preferences in recommendation tasks based on tensor factorization.

# Useful keywords

- concept drift
- preference/interest shift
- temporal dynamics/evolution
- time-aware recommender systems
- temporal recommender systems
- non-stationary learning