CSE 158 – Lecture 17

Web Mining and Recommender Systems

Temporal data mining

This week

Temporal models

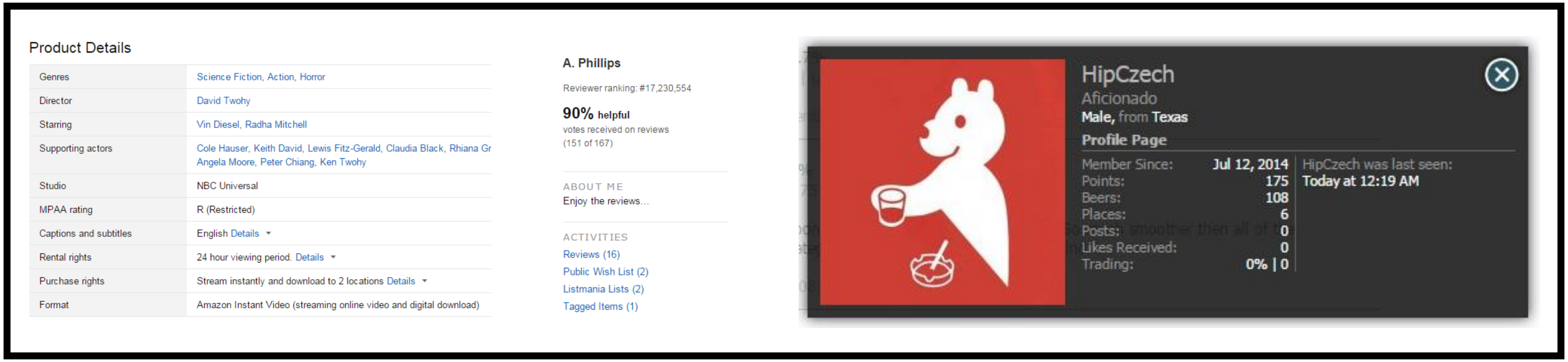
This week we'll look back on some of the topics already covered in this class, and see how they can be adapted to make use of **temporal** information

1. **Regression** – sliding windows and autoregression
2. **Classification** – dynamic time-warping
3. **Dimensionality reduction** - ?
4. **Recommender systems** – some results from Koren

Next lecture:

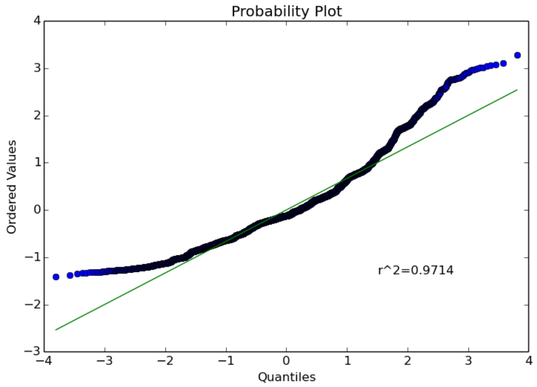
1. **Text mining** – "Topics over Time"
2. **Social networks** – densification over time

1. Regression



How can we use **features** such as product properties and user demographics to make predictions about **real-valued** outcomes (e.g. star ratings)?

How can we prevent our models from **overfitting** by favouring simpler models over more complex ones?



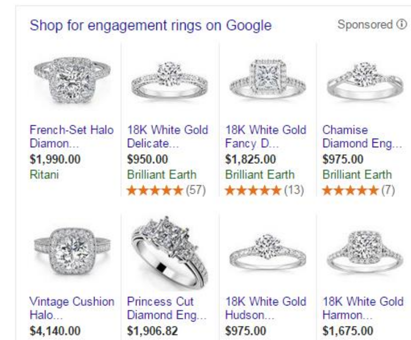
How can we assess our decision to optimize a particular error measure, like the MSE?

2. Classification

Next we adapted these ideas to **binary** or **multiclass** outputs

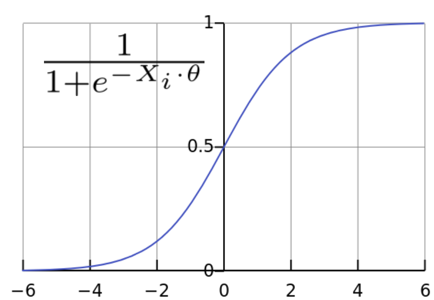
What animal is in this image?

Will I **purchase** this product?

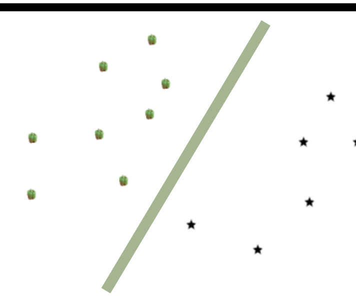


Will I **click on** this ad?

Combining features using naïve Bayes models

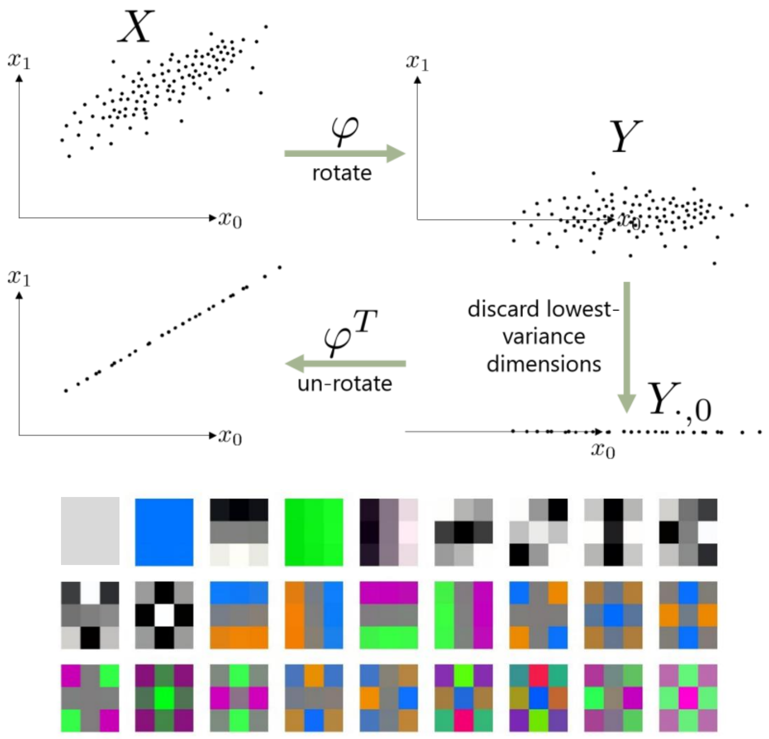


Logistic regression

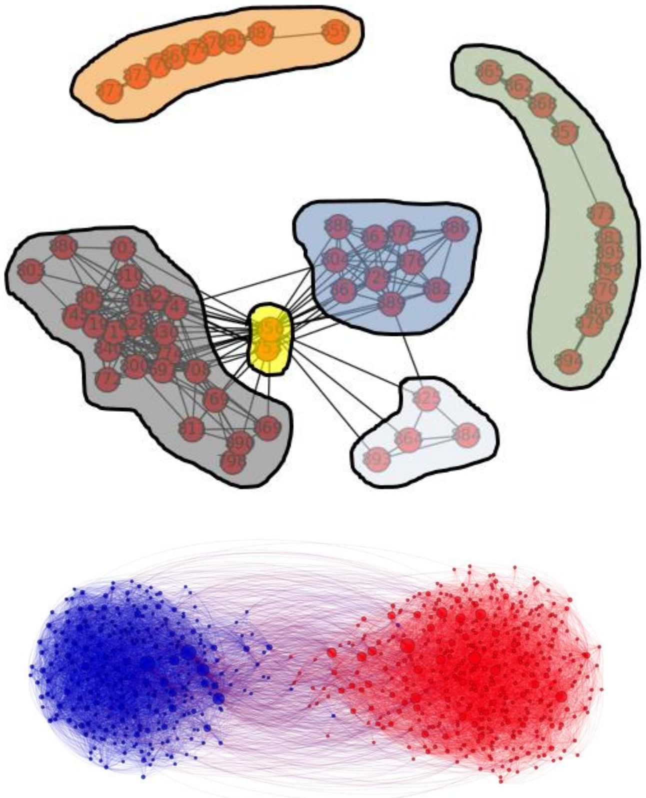


Support vector machines

3. Dimensionality reduction



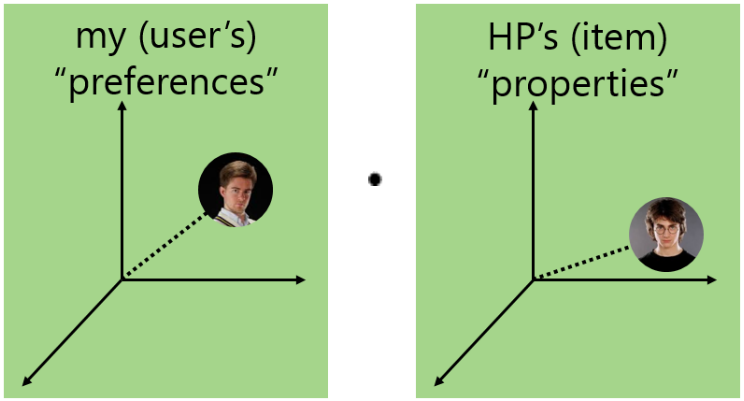
Principal component analysis

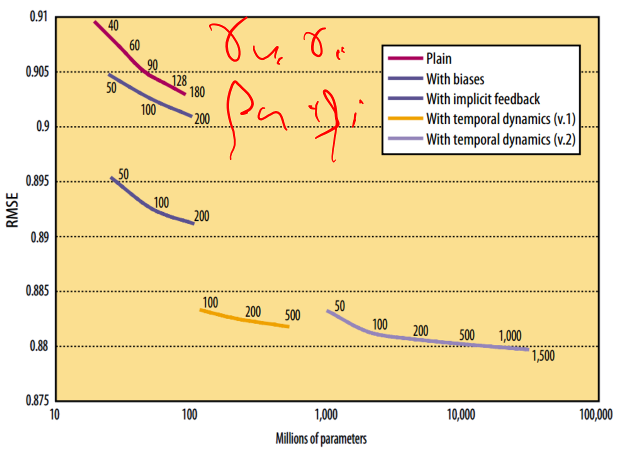


Community detection

4. Recommender Systems

Rating distributions and the missing-not-at-random assumption





Latent-factor models

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Regression for sequence data

Week 1 – Regression

Given **labeled training data** of the form

$$\{(\text{data}_1, \text{label}_1), \ldots, (\text{data}_n, \text{label}_n)\}$$

Infer the function

$$f(\text{data}) \stackrel{?}{\rightarrow} \text{labels}$$

Time-series regression

Here, we'd like to predict sequences of **real-valued** events as accurately as possible.

$$\underbrace{x_1 \;\ldots\; x_m}_{\text{"data"}} \quad \underbrace{x_{m+1}}_{\text{label}} \quad \underbrace{x_{m+2}}_{\text{label}}$$

$$\underbrace{x_1 \;\ldots\; x_m \quad x_{m+1}}_{\text{data}}$$

$$f(x_1 \;\ldots\; x_m) \rightarrow x_{m+1}$$

Time-series regression

Method 1: maintain a "moving average" using a window of some fixed length

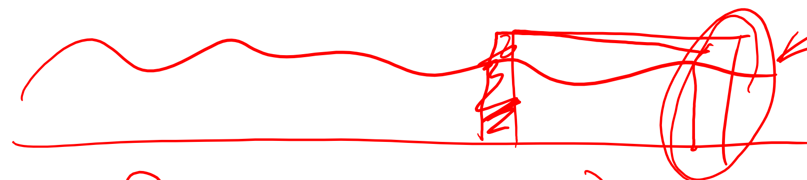
$$f(x_1, \ldots, x_m) = \frac{x_m + x_{m-1} + x_{m-2} \cdots + x_{m-k+1}}{k}$$

$O(m \times k)$

Time-series regression

Method 1: maintain a "moving average" using a window of some fixed length

- This can be computed efficiently via dynamic programming:



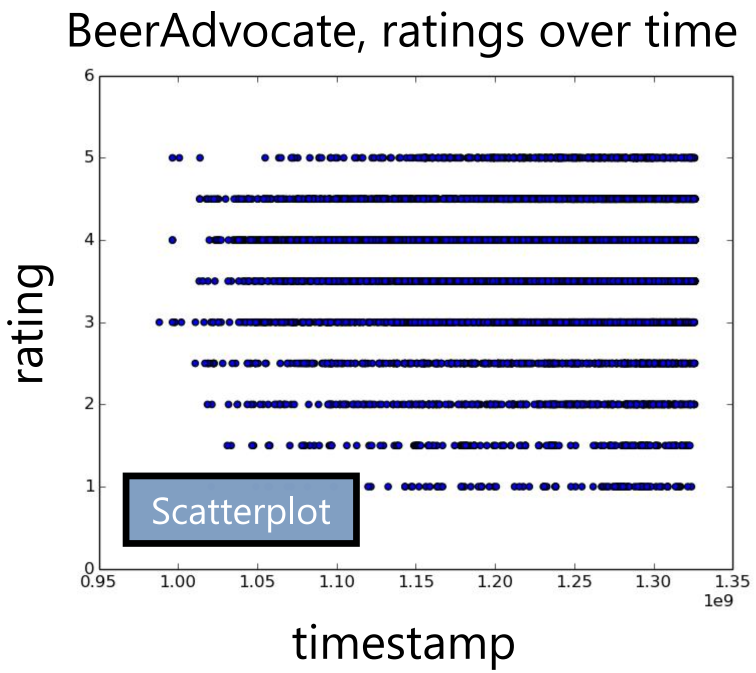
x_{m+1}

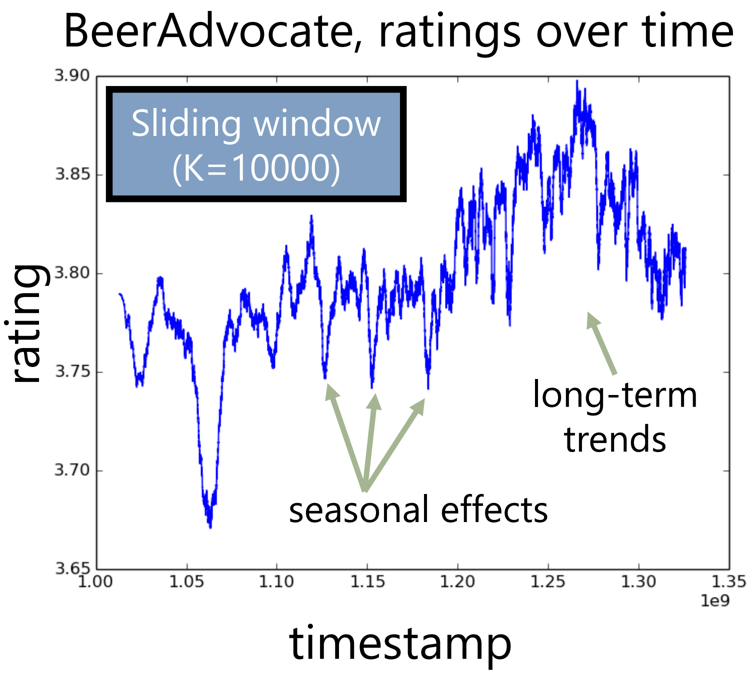
$$f(x_1, \ldots, x_{m+1}) = \frac{K f(x_1, \ldots, x_m) - x_{m-K+1} + x_m}{K}$$

$O(m+K)$ vs. $O(mK)$

Time-series regression

Also useful to plot data:





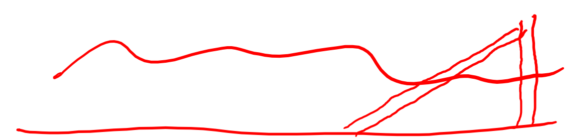
Code on:

http://jmcauley.ucsd.edu/code/week10.py

Method 2: weight the points in the moving average by age

$$f(x_1, \ldots, x_m) = \frac{K x_m + (K-1) x_{m-1} + (K-2) x_{m-2} \ldots 1 \times x_{m-K+1}}{1+2+3+4 \ldots K}$$

$$= \frac{\sum_{k=0}^{K-1} (K-k) x_{m-k}}{\binom{K}{2}}$$



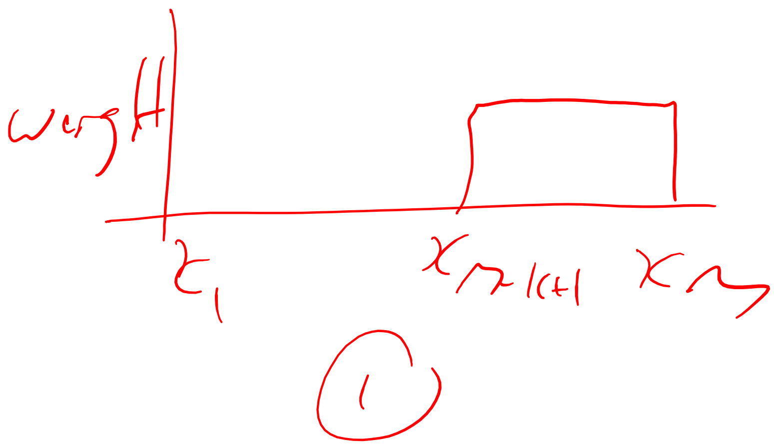
Method 3: weight the most recent points exponentially higher

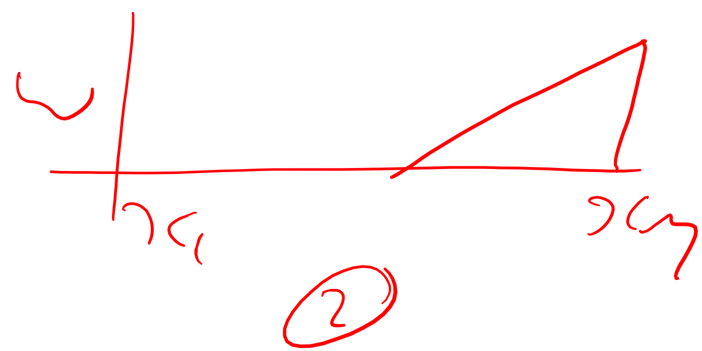
$$f(x_1) = x_1$$

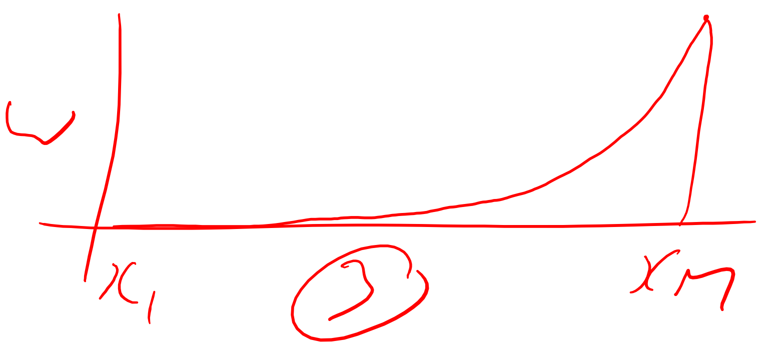
$$f(x_1, \ldots, x_m) = \alpha x_m + (1-\alpha) f(x_1, \ldots, x_{m-1})$$

Methods 1, 2, 3

Method 1: Sliding window
Method 2: Linear decay
Method 3: Exponential decay







Method 4: all of these models are assigning **weights** to previous values using some predefined scheme, why not just **learn** the weights?

$$f_\theta(x_1, \ldots, x_m) = \theta_0 x_m + \theta_1 x_{m-1} + \theta_2 x_{m-2} \ldots \theta_{k-1} x_{m-k+1}$$

$$\sum_{k=0}^{k-1} \theta_k x_{m-k}$$

$$\min_\theta \sum_i \left(f_\theta(x_1 \ldots x_i) - x_{i+1}\right)^2$$

Time-series regression

Method 4: all of these models are assigning **weights** to previous values using some predefined scheme, why not just **learn** the weights?

- We can now fit this model using least-squares
- This procedure is known as **autoregression**
- Using this model, we can capture **periodic** effects, e.g. that the traffic of a website is most similar to its traffic 7 days ago

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Web Mining and Recommender Systems

Classification of sequence data

Week 2

How can we predict **binary** or **categorical** variables?

$$f(\text{data}) \stackrel{?}{\rightarrow} \text{labels}$$

{0,1}, {True, False}

{1, … , N}

Another simple algorithm: nearest neighbo(u)rs

Time-series classification

As you recall…
The longest-common subsequence algorithm is
a standard dynamic programming problem

	-	A	G	C	A	T
-	0	0	0	0	0	0
G	0	0	1	1	1	1
A	0	1	1	1	2	2
C	0	1	1	2	2	2

1st sequence

2nd sequence

Time-series classification

As you recall…
The longest-common subsequence algorithm is a standard dynamic programming problem

	-	A	G	C	A	T
-	0	0	0	0	0	0
G	0	←↑ 0	↖ 1	← 1	← 1	← 1
A	0	↖ 1	←↑ 1	←↑ 1	↖ 2	← 2
C	0	↑ 1	←↑ 1	↖ 2	←↑ 2	←↑ 2

1st sequence

2nd sequence

← = optimal move is to delete from 1st sequence

↑ = optimal move is to delete from 2nd sequence

←↑ = either deletion is equally optimal

↖ = optimal move is a match

Time-series classification

The same type of algorithm is used to find correspondences between time-series data (e.g. speech signals), whose length may vary in time/speed

```
DTW_cost = infty
for i in range(1,N):
  for j in range(1,M):
    d = dist(s[i], t[j]) # Distance between
sequences s and t and points i and j
    DTW[i,j] = d + min(DTW[i-1, j  ],
                       DTW[i,   j-1],
                       DTW[i-1, j-1]
return DTW[N,M]
```

skip from seq. 1

skip from seq. 2

match

output is a **distance** between the two sequences

Time-series classification

- This is a simple procedure to infer the similarity between sequences, so we could classify them (for example) using nearest-neighbours (i.e., by comparing a sequence to others with known labels)

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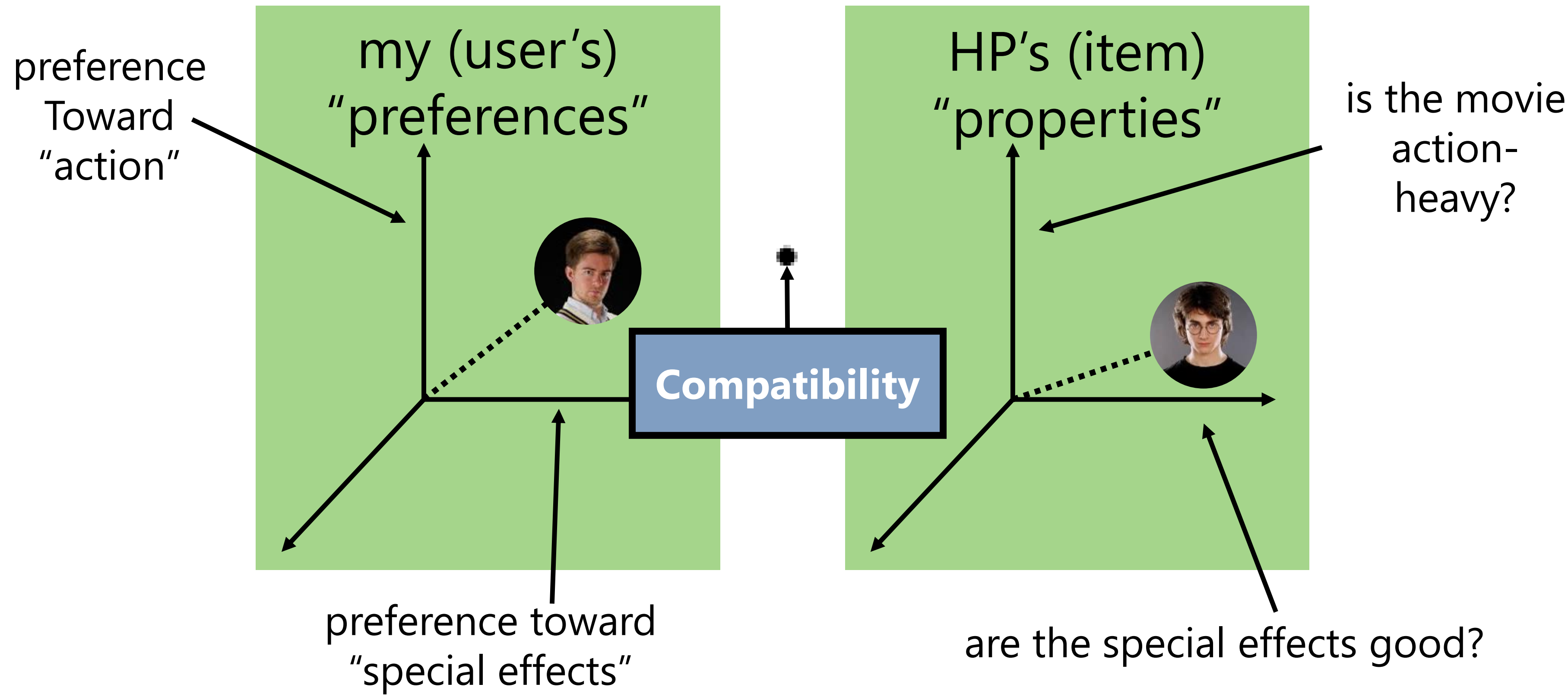
Web Mining and Recommender Systems

Temporal recommender systems

Week 4/5

Recommender Systems go beyond the methods we've seen so far by trying to model the **relationships** between people and the items they're evaluating



Week 4/5

Predict a user's rating of an item according to:

$$f(u,i) = \alpha + \beta_u + \beta_i + \gamma_u \cdot \gamma_i$$

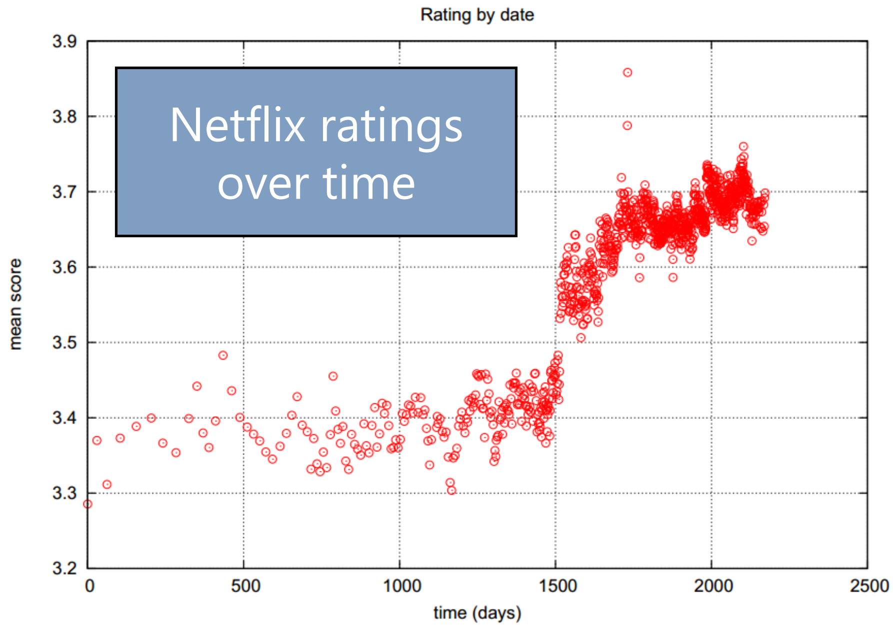
By solving the optimization problem:

$$\arg\min_{\alpha,\beta,\gamma} \underbrace{\textstyle\sum_{u,i}(\alpha+\beta_u+\beta_i+\gamma_u\cdot\gamma_i-R_{u,i})^2}_{\text{error}}+\lambda \underbrace{\left[\textstyle\sum_u \beta_u^2 + \sum_i \beta_i^2 + \sum_i \|\gamma_i\|_2^2 + \sum_u \|\gamma_u\|_2^2\right]}_{\text{regularizer}}$$

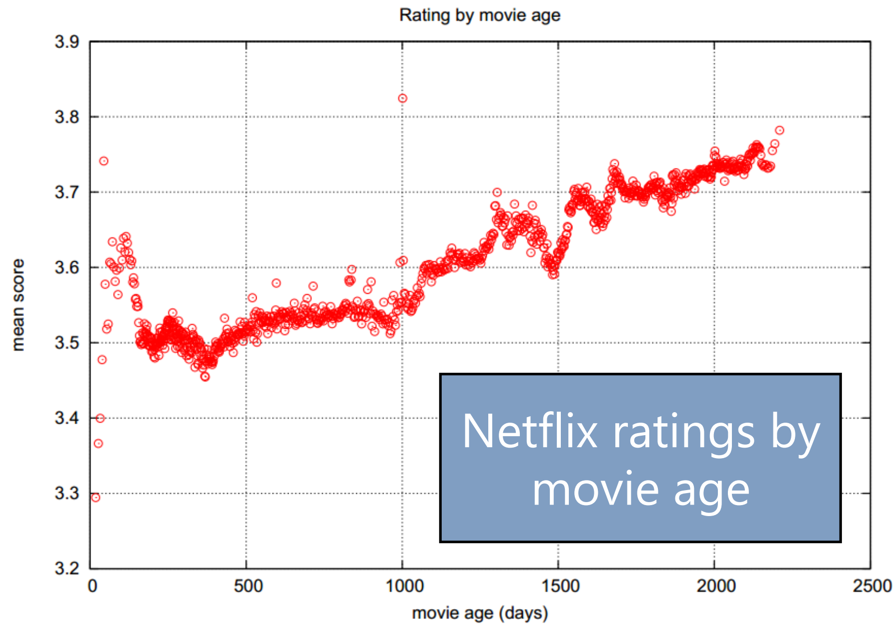
(e.g. using stochastic gradient descent)

Temporal latent-factor models

To build a reliable system (and to win the Netflix prize!) we need to account for **temporal dynamics:**



(Netflix changed their interface)



(People tend to give higher ratings to older movies)

So how was this actually done?

Figure from Koren: “Collaborative Filtering with Temporal Dynamics” (KDD 2009)

Temporal latent-factor models

To start with, let's just assume that it's only the **bias** terms that explain these types of temporal variation (which, for the examples on the previous slides, is potentially enough)

$$b_{u,i}(t) = \alpha + \beta_u(t) + \beta_i(t)$$

Idea: temporal dynamics for *items* can be explained by long-term, gradual changes, whereas for users we'll need a different model that allows for "bursty", short-lived behavior

Temporal latent-factor models

temporal bias model:

$$b_{u,i}(t) = \alpha + \beta_u(t) + \beta_i(t)$$

For item terms, just separate the dataset into (equally sized) bins:*

$$\beta_i(t) = \beta_i + \beta_{i,\mathrm{Bin}(t)}$$

*in Koren's paper they suggested ~30 bins corresponding to about 10 weeks each for Netflix

or bins for periodic effects (e.g. the day of the week):

$$\beta_i(t) = \beta_i + \beta_{i,\mathrm{Bin}(t)} + \beta_{i,\mathrm{period}(t)}$$

What about user terms?

- We need something much finer-grained
- **But** – for most users we have far too little data to fit very short term dynamics

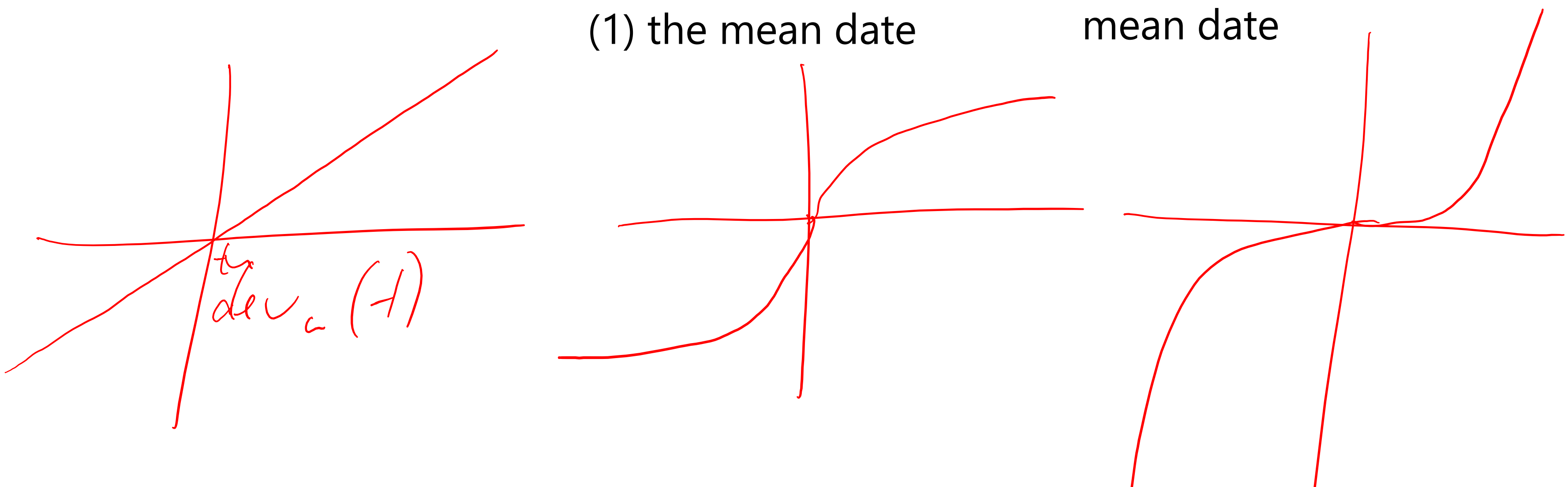
Temporal latent-factor models

Start with a simple model of drifting dynamics for users:

mean rating date for user u

hyperparameter (ended up as x=0.4 for Koren)

$$\mathrm{dev}_u(t) = \underbrace{\mathrm{sign}(t - t_u)}_{\text{before (-1) or after (1) the mean date}} \cdot \underbrace{|t - t_u|}_{\text{days away from mean date}}^{x}$$



Temporal latent-factor models

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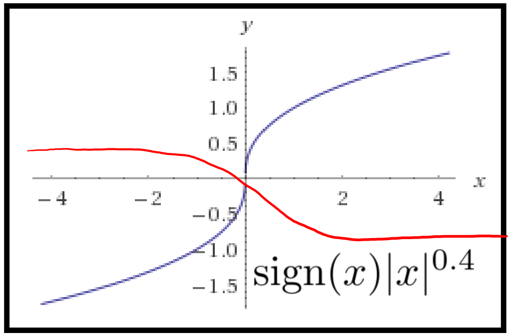
$$\mathrm{dev}_u(t) = \underbrace{\mathrm{sign}(t - t_u)}_{\text{before (-1) or after (1) the mean date}} \cdot \underbrace{|t - t_u|}_{\text{days away from mean date}}{}^{x}$$

time-dependent user bias can then be defined as:

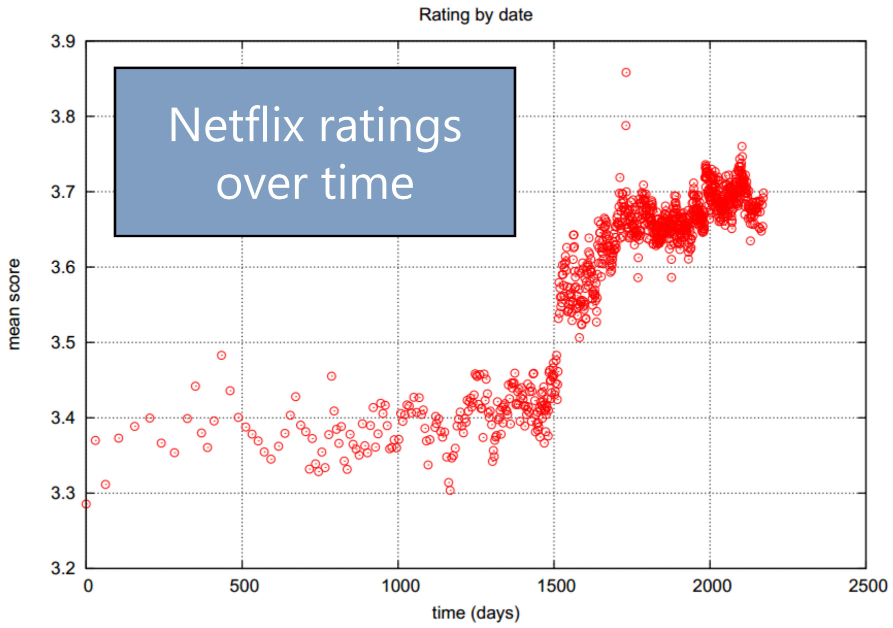
$$\beta_u^{(1)}(t) = \beta_u + \alpha_u \cdot \mathrm{dev}_u(t)$$

overall user bias

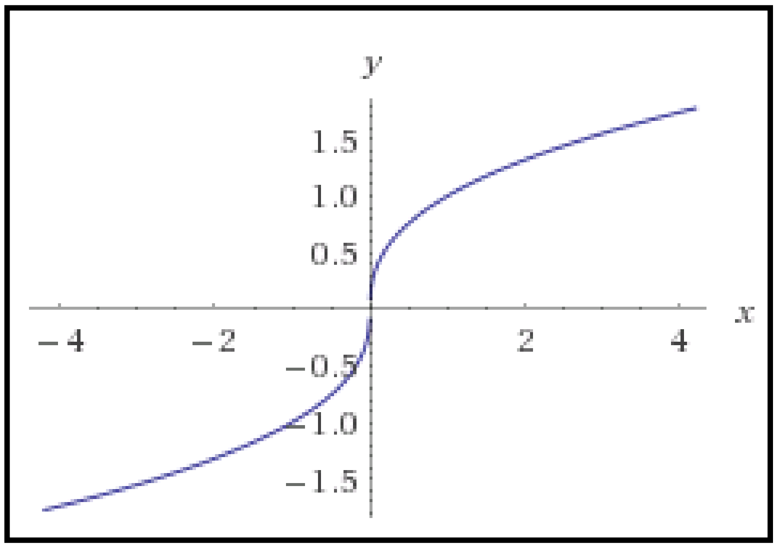
sign and scale for deviation term



Temporal latent-factor models



Real data



Fitted model

Temporal latent-factor models

time-dependent user bias can then be defined as:

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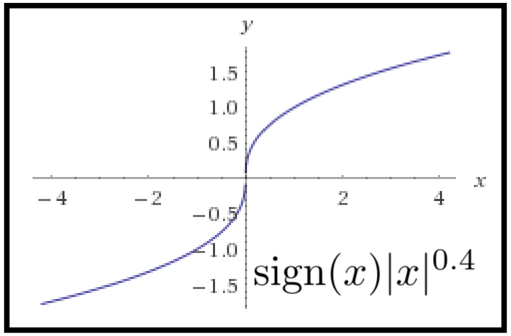
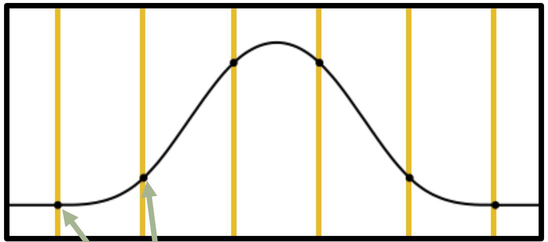


- Requires only two parameters per user and captures some notion of temporal “drift” (even if the model found through cross-validation is (to me) completely unintuitive)
- To develop a slightly more expressive model, we can interpolate smoothly between biases using splines



control points

Temporal latent-factor models

number of control points for this user
(k_u = n_u^0.25 in Koren)

user bias associated with this control point

$$\beta_u^{(2)}(t) = \beta_u + \frac{\sum_{l=1}^{k_u} e^{-\gamma|t - t_l^u|} b_{t_l}^u}{\sum_{l=1}^{k_u} e^{-\gamma|t - t_l^u|}}$$

time associated with control point
(uniformly spaced)

Temporal latent-factor models

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(k_u = n_u^0.25 in Koren)

user bias associated with this control point

$$\beta_u^{(2)}(t) = \beta_u + \frac{\sum_{l=1}^{k_u} e^{-\gamma|t-t_l^u|} b_{t_l}^u}{\sum_{l=1}^{k_u} e^{-\gamma|t-t_l^u|}}$$

time associated with control point
(uniformly spaced)

- This is now a reasonably flexible model, but still only captures *gradual drift*, i.e., it can't handle sudden changes (e.g. a user simply having a bad day)

Temporal latent-factor models

- Koren got around this just by adding a "per-day" user bias:

$$\beta_{u,t}$$

bias for a particular day (or session)

- Of course, this is only useful for particular days in which users have a lot of (abnormal) activity
- The final (time-evolving bias) model then combines all of these factors:

global offset

gradual deviation (or splines)

item bias

gradual item bias drift

$$\beta_{u,i}(t) = \alpha + \beta_u + \alpha_u \cdot \mathrm{dev}_u(t) + \beta_{u,t} + \beta_i + \beta_{i,\mathrm{Bin}(t)}$$

user bias

single-day dynamics

Temporal latent-factor models

Finally, we can add a time-dependent scaling factor:

$$\beta_{u,i}(t) = \alpha + \beta_u + \alpha_u \cdot \mathrm{dev}_u(t) + \beta_{u,t} + (\beta_i + \beta_{i,\mathrm{Bin}(t)}) \cdot c_u(t)$$

also defined as $c_u + c_{u,t}$

Latent factors can also be defined to evolve in the same way:

$$\gamma_{u,k}(t) = \gamma_{u,k} + \alpha_{u,k} \cdot \mathrm{dev}_u(t) + \gamma_{u,k,t}$$

factor-dependent
user drift

factor-dependent
short-term effects

Temporal latent-factor models

Summary

- Effective modeling of temporal factors was absolutely critical to this solution outperforming alternatives on Netflix's data
  - In fact, even with only temporally evolving *bias* terms, their solution was already ahead of Netflix's previous ("Cinematch") model

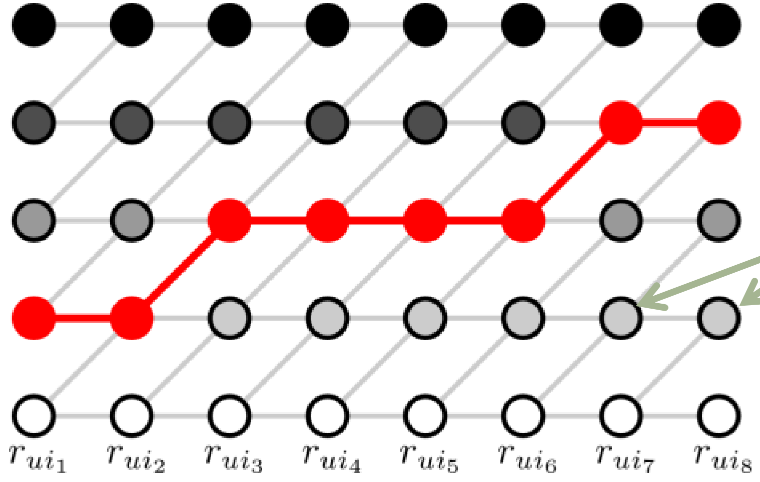
On the other hand…

- Many of the ideas here depend on dynamics that are quite specific to "Netflix-like" settings
- Some factors (e.g. short-term effects) depend on a high density of data per-user and per-item, which is not always available

Summary

- Changing the setting, e.g. to model the stages of progression through the symptoms of a disease, or even to model the temporal progression of people's opinions on beers, means that alternate temporal models are required

rows: models of increasingly "experienced" users



columns: review timeline for one user

Questions?

Further reading:
"Collaborative filtering with temporal dynamics"
Yehuda Koren, 2009
http://research.yahoo.com/files/kdd-fp074-koren.pdf