

# Machine Learning

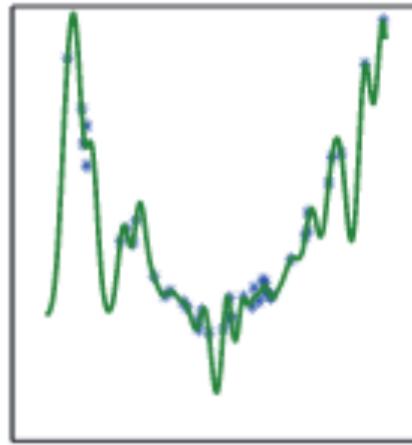
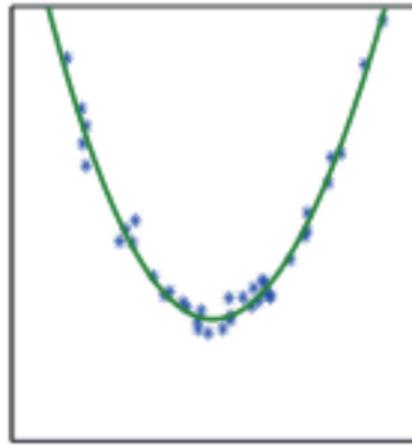
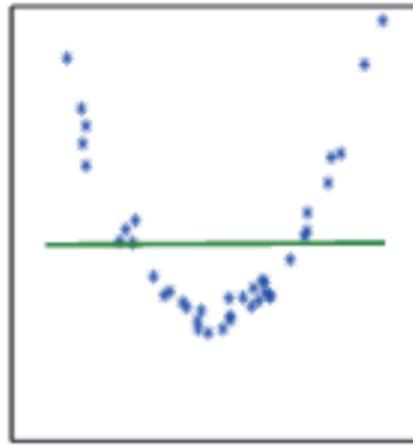
Time Series (continued), Recommendation, NLP

Jeff Abrahamson

Cours sur l'année, 2017–2018

# Review

# Underfitting, overfitting



# Linear Regression

# Logistic Regression

# SVM

# CART

# **Random Forests**

# PCA

# Handwriting Recognition

# Clustering

## Anomaly Detection (not time)

## Anomaly detection (not time)

- Supervised (usually): normal / not-normal
- Mostly clustering: *k*-means, kNN, LOF, SVM

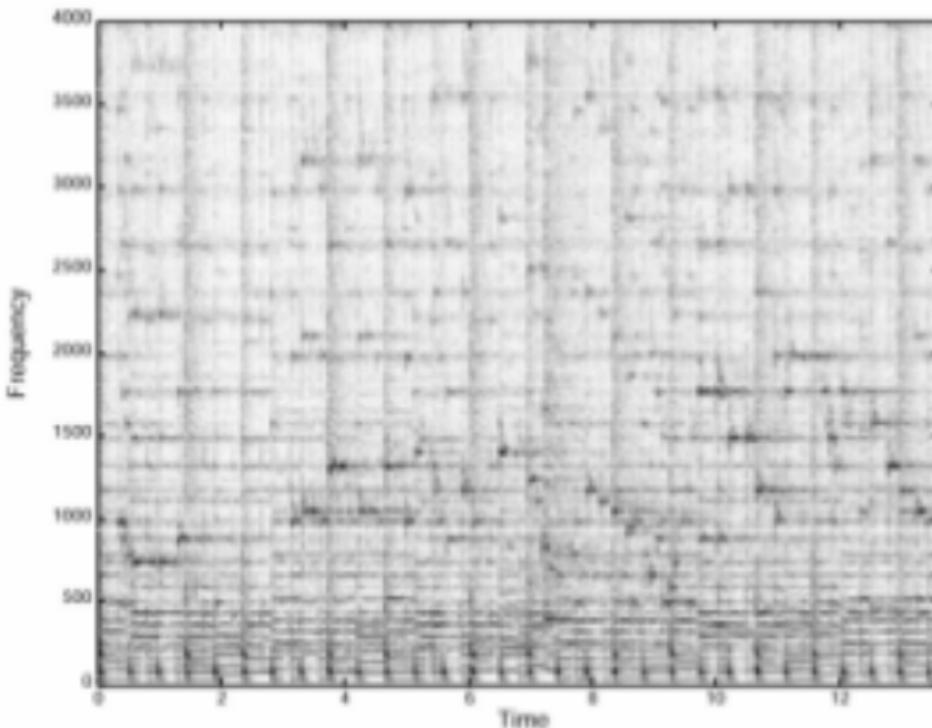


Fig. 1A - Spectrogram

<https://www.ee.columbia.edu/~dpwe/papers/Wang03-shazam.pdf>

Copyright 2017–2018 Jeff Abrahamson, for private use by course students only

ML Week

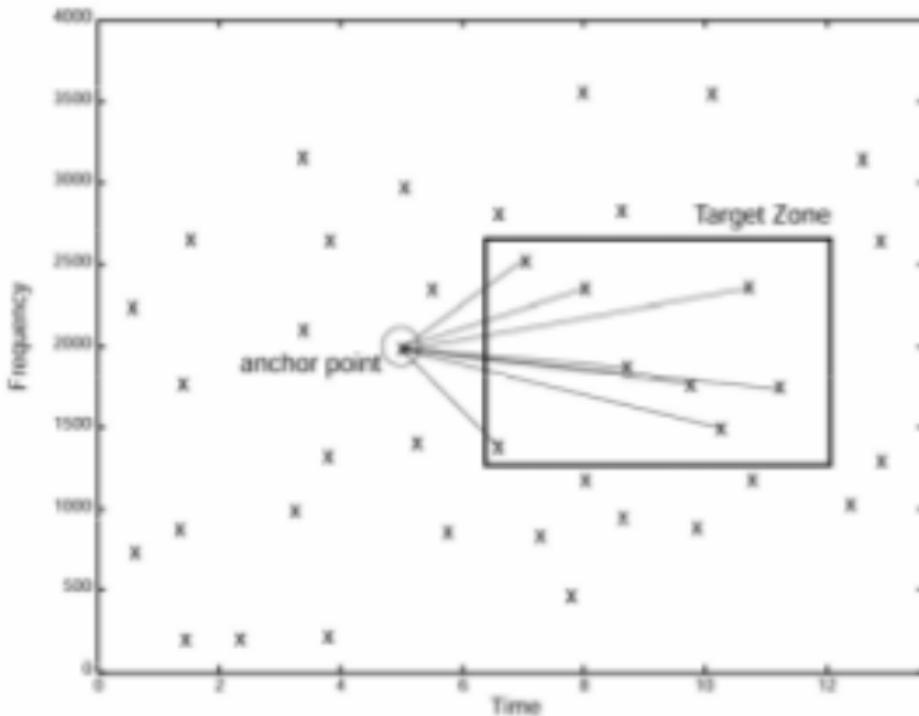


Fig. 1C - Combinatorial Hash Generation

<https://www.ee.columbia.edu/~dpwe/papers/Wang03-shazam.pdf>

Copyright 2017–2018 Jeff Abrahamson, for private use by course students only

ML Week

# Time Series

# Introduction to time series

Why?

- Predict
- Control
- Understand
- Describe

# Introduction to time series

Some strategies:

- Differencing:

$$y'_t = y_t - y_{t-1}$$

- Second-order differencing:

$$y''_t = (y_t - y_{t-1}) - (y_{t-1} - y_{t-2}) = y_t - 2y_{t-1} + y_{t-2}$$

# Introduction to time series

Some strategies:

- Clustering
- Hidden Markov Models (HMM)
- Recurrent neural networks (RNN)
- Autoregressive integrated moving average (ARIMA)
  - Generalisation of autoregressive moving average (ARMA) model
  - Regress on series' own lag

# Introduction to time series

One model:

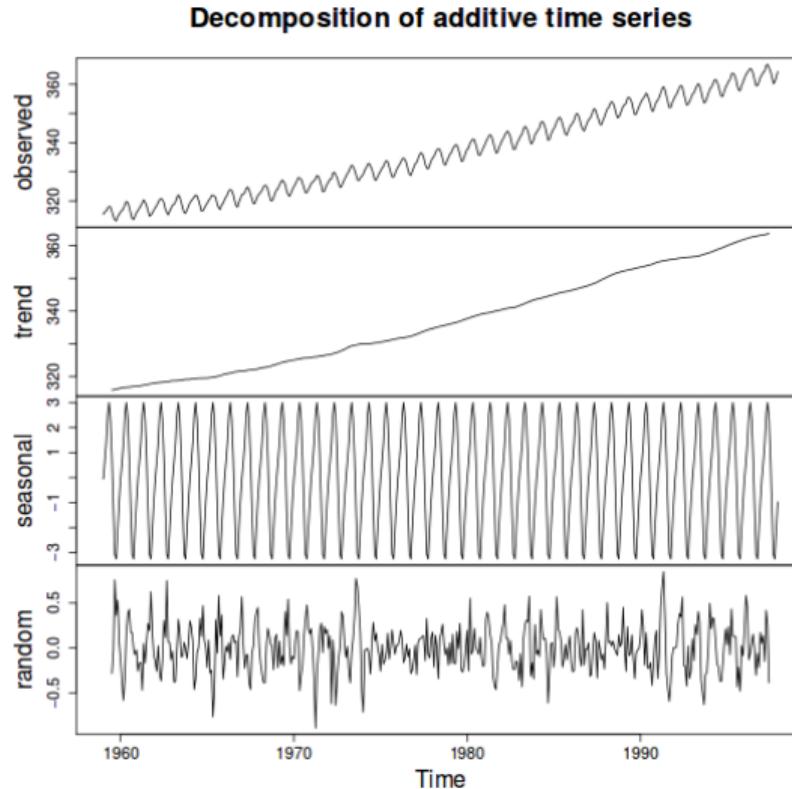
$$s_t = g(t) + \phi_t$$

where

$g(t)$  is deterministic: signal (or trend)

$\phi_t$  is stochastic noise

# Introduction to time series



[http://www.ulb.ac.be/di/map/gbonte/ftp/time\\_ser.pdf](http://www.ulb.ac.be/di/map/gbonte/ftp/time_ser.pdf)

Copyright 2017–2018 Jeff Abrahamson, for private use by course students only

ML Week

# Introduction to time series

Some easy things to try

- Introduce features to break out seasonality
- Introduce lags as features
- Some domain-specific transformation

**HMM**

# Recommendation

# Definition

Given data about a user, his environment, and some items of interest (*training data*), determine items to recommend.

# Definition

Given data about a user, his environment, and some items of interest (*training data*), determine items to recommend.

We don't have to find the max  $k$ .

It's enough to find  $k$  within some max  $n$ .

# Examples

- Amazon
- Google News (or Le Monde)
- Facebook
- Medical testing
- App Store / Google Play
- Youtube
- Advertising
- Netflix, last.fm, Spotify, Pandora, ...
- Browser (URL recommendations)
- Search

# Client Value Proposition

- Find opportunities
- Reduce choice
- Explore options
- Discover long tails
- Recreation

# Provider Value Proposition

- Offer a unique or additional service (beyond competitors)
- Customer trust and loyalty
- Increase sales, CTR, conversions
- Better understand customers

# Recommendation

Content-based filtering <i>(filtrage basée sur le continu)</i>	More things similar to what I like
Collaborative filtering <i>(filtrage collaboratif)</i>	More of what other people who like what I like like
Knowledge-based filtering <i>(filtrage basée sur connaissance)</i>	More of what I need.

# Content-based filtering

*More things similar to what I like*

*Plus de ce qui ressemble à ce que j'aime*

## Advantages

**yes!** No need for community

**yes!** Possible to compare items

## Disadvantages

**no** Understand content

**yes** Cold start problem

**no** Serendipity

# Collaborative filtering

*More of what other people who like what I like like*

*Plus de ce que d'autres qui aiment ce que j'aime aiment*

## Advantages

yes! No need to understand content

yes! Serendipity

yes! Learn market

## Disadvantages

no User feedback

yes Cold start problem (users)

yes Cold start problem (items)

# Knowledge-based filtering

*More of what I need  
Plus de ce qu'il faut*

## Advantages

yes! Deterministic

yes! Certainty

no! Cold start problem

yes! Market knowledge

## Disadvantages

yes Studies to bootstrap

yes Static model, doesn't learn from trends

# Utility Matrix

- Users (utilisateurs)
- Items (objets)

# Utility Matrix

- Users (utilisateurs)
- Items (objets)

The goal is to fill in the blanks.

	$I_1$	$I_2$	$I_3$	$I_4$	$I_5$
$U_1$	1				
$U_2$		1	1	1	
$U_3$		1	1	1	

Example: books sales at Amazon.

*But thousands or millions of columns and rows.*

# Utility Matrix

- Users (utilisateurs)
- Items (objets)

The goal is to fill in the blanks.

	$I_1$	$I_2$	$I_3$	$I_4$	$I_5$
$U_1$	3				
$U_2$		5	1	4	
$U_3$		2	5	1	

Example: film advice at Netflix.

*But thousands or millions of columns and rows.*

# Utility Matrix

How do we make the matrix?

- Ask users
- Observe users

That's usually expensive...

# Item Profiles

Examples:

- Films       $\Rightarrow ?$
- Books       $\Rightarrow ?$
- News       $\Rightarrow ?$
- Images       $\Rightarrow ?$

# Item Profiles

Examples:

- Films       $\Rightarrow ?$
- Books       $\Rightarrow ?$
- News       $\Rightarrow ?$
- Images       $\Rightarrow ?$

Films :

Content: actors, directors, year (decade, etc.), length

Collaborative: seen, opinion (1–5), when seen relative to release

# Item Profiles

Examples:

- Films       $\Rightarrow ?$
- Books       $\Rightarrow ?$
- News       $\Rightarrow ?$
- Images       $\Rightarrow ?$

Books:

Content : authers, genre, year (decade, etc.), number of pages, content (very difficult)

Collaborative: read, opinion (1–5), how read

# Item Profiles

Examples:

- Films       $\Rightarrow ?$
- Books       $\Rightarrow ?$
- News       $\Rightarrow ?$
- Images       $\Rightarrow ?$

News:

Content : source, section, TF-IDF word vectors

Collaborative:

# Item Profiles

Examples:

- Films       $\Rightarrow ?$
- Books       $\Rightarrow ?$
- News       $\Rightarrow ?$
- Images       $\Rightarrow ?$

Images :

Content:

Collaborative:

# Item Profiles

Examples:

- Films       $\Rightarrow ?$
- Books       $\Rightarrow ?$
- News       $\Rightarrow ?$
- Images       $\Rightarrow ?$

Also: user profile, user behavior

# Mathematics

Vectors

Similarity

# Similarity : Jaccard Index

or: *Indice de Jaccard, Jaccard similarity coefficient*

Similarity:

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|}$$

# Similarity : Jaccard Index

Similarity:

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|}$$

Distance:

$$J_\delta(A, B) = 1 - J(A, B)$$

# cosine similarity

or: *mesure cosinus*, *Similarité cosinus*

Similarity:

$$\cos \theta = \frac{A \cdot B}{\| A \| \| B \|}$$

# cosine similarity

Similarity:

$$S_C(A, B) = \frac{A \cdot B}{\| A \| \| B \|}$$

# cosine similarity

Similarity:

$$S_C(A, B) = \frac{A \cdot B}{\| A \| \| B \|}$$

Distance:

$$D_C(A, B) = 1 - S_C(A, B)$$

# cosine similarity

Similarity:

$$S_C(A, B) = \frac{A \cdot B}{\| A \| \| B \|}$$

Distance:

$$D_C(A, B) = 1 - S_C(A, B)$$

We only consider non-empty components in the vector.

## Texts: TF-IDF

- Vectors of word frequencies
- Frequency  $\not\Rightarrow$  significance

## Texts: TF-IDF

- Vectors of word frequencies
- Frequency  $\not\Rightarrow$  significance
- Term Frequency - Inverse Document Frequency

## Texts: TF-IDF

$$TF_{ij} = \frac{f_{ij}}{\max_k f_{kj}} \quad IDF_I = \log_2 \left( \frac{N}{n_i} \right)$$

$$TF-IDF_{ij} = TF_{ij} \cdot IDF_i$$

with :

$f_{ij}$  = frequency of word  $i$  in document  $j$

$N$  = number of documents

$n_i$  = number of documents in which we find word  $i$

## Texts: TF-IDF

$$TF_{ij} = \frac{f_{ij}}{\max_k f_{kj}} \quad IDF_I = \log_2 \left( \frac{N}{n_i} \right)$$

$$TF-IDF_{ij} = TF_{ij} \cdot IDF_i$$

with :

$f_{ij}$  = frequency of word  $i$  in document  $j$

$N$  = number of documents

$n_i$  = number of documents in which we find word  $i$

IDF is a measure of how much information a word carries

TF-IDF tells us which words best characterise a document

## Texts: TF-IDF

$$TF_{ij} = \frac{f_{ij}}{\max_k f_{kj}} \quad IDF_I = \log_2 \left( \frac{N}{n_i} \right)$$

$$TF-IDF_{ij} = TF_{ij} \cdot IDF_i$$

with :

$f_{ij}$  = frequency of word  $i$  in document  $j$

$N$  = number of documents

$n_i$  = number of documents in which we find word  $i$

IDF is a measure of how much information a word carries

TF-IDF tells us which words best characterise a document

Variation: boolean, log, stop word filtering

# Content-Based Filtering

	$I_1$	$I_2$	$I_3$	$I_4$	$I_5$
$U_1$	3				
$U_2$		5	1	4	
$U_3$	2		5	1	

More things similar to what I like  
*Plus de ce qui ressemble à ce que j'aime*

# Content-Based Filtering

	$I_1$	$I_2$	$I_3$	$I_4$	$I_5$
$U_1$	3				
$U_2$		5	1	4	
$U_3$	2		5	1	

More things similar to what I like  
*Plus de ce qui ressemble à ce que j'aime*

Then, we can cluster (*regroupement, partitionnement de données*), etc.

# Content-Based Filtering

Based on item profiles

- More stable (in principle)
- $O(n^2)$  (but often less, items often aren't categorised together)
- Can reduce to threshold
- Can pre-calculate, queries become faster

# Collaborative Filtering

	$I_1$	$I_2$	$I_3$	$I_4$	$I_5$
$U_1$	3		4	2	
$U_2$		5	1	4	
$U_3$	2		5	1	

More of what other people who like what I like like  
*Plus de ce que d'autres qui aiment ce que j'aime aiment*

# Collaborative Filtering

	$I_1$	$I_2$	$I_3$	$I_4$	$I_5$
$U_1$	3				
$U_2$		5	1	4	
$U_3$	2		5	1	

User profile

# Collaborative Filtering

	$I_1$	$I_2$	$I_3$	$I_4$	$I_5$
$U_1$	3		4	2	
$U_2$			5	1	4
$U_3$		2		5	1

Item profile

# Utility Matrix Symmetry

- Propose items based on users
- Propose users based on items

# Utility Matrix Symmetry

- Propose items based on users
- Propose users based on items

But remember: **2 items being similar  $\not\equiv$  2 users similar.**

# Utility Matrix Symmetry

- Propose items based on users
- Propose users based on items

But remember: 2 items being similar  $\not\equiv$  2 users similar.

Thought experiment: consider comparing people vs comparing objects.

# Utility Matrix Symmetry

- Propose items based on users
- Propose users based on items

To estimate  $m_{u,i}$ ,

- Find  $k$  users like  $U_u$
- Find  $k$  items like  $I_i$

## Utility Matrix : Estimate $m_{u,i}$

	$I_1$	$I_2$	$I_3$	$I_4$	$I_5$
$U_1$	3		4	2	<input type="text"/>
$U_2$			5	1	4
$U_3$		2		2	3

- Find  $k$  users like  $U_u$ , take  $\frac{1}{k} \sum_{j=1}^k m_{u_j,i}$
- Find  $k$  items like  $I_i$ , take  $\frac{1}{k} \sum_{j=1}^k m_{u,i_j}$

## Utility Matrix : Estimate $m_{u,i}$

	$I_1$	$I_2$	$I_3$	$I_4$	$I_5$
$U_1$	3		4	2	<input type="text"/>
$U_2$			5	1	4
$U_3$		2		2	3

- Find  $k$  users like  $U_u$ , take  $\frac{1}{k} \sum_{j=1}^k m_{u_j,i}$
- Find  $k$  items like  $I_i$ , take  $\frac{1}{k} \sum_{j=1}^k m_{u,i_j}$

We have to compute the entire line (or the part which is likely to be important)

## Utility Matrix : Estimate $m_{u,i}$

	$I_1$	$I_2$	$I_3$	$I_4$	$I_5$
$U_1$	3		4	2	<input type="text"/>
$U_2$			5	1	4
$U_3$		2		2	3

- Find  $k$  users like  $U_u$ , take  $\frac{1}{k} \sum_{j=1}^k m_{u_j,i}$
- Find  $k$  items like  $I_i$ , take  $\frac{1}{k} \sum_{j=1}^k m_{u,i_j}$

Once we've computed  $U_u$ , the other  $k$  users lets us take a shortcut.

## Utility Matrix : Estimate $m_{u,i}$

	$I_1$	$I_2$	$I_3$	$I_4$	$I_5$
$U_1$	3		4	2	<input type="text"/>
$U_2$			5	1	4
$U_3$		2		2	3

- Find  $k$  users like  $U_u$ , take  $\frac{1}{k} \sum_{j=1}^k m_{u_j,i}$
- Find  $k$  items like  $I_i$ , take  $\frac{1}{k} \sum_{j=1}^k m_{u,i_j}$

For  $I_i$ , we have to compute most of the  $I_j$  before we can fill in a single line. But item-item filters are often more reliable.

## Utility Matrix : Estimate $m_{u,i}$

	$I_1$	$I_2$	$I_3$	$I_4$	$I_5$
$U_1$	3		4	2	<input type="text"/>
$U_2$			5	1	4
$U_3$		2		2	3

- Find  $k$  users like  $U_u$ , take  $\frac{1}{k} \sum_{j=1}^k m_{u_j,i}$
- Find  $k$  items like  $I_i$ , take  $\frac{1}{k} \sum_{j=1}^k m_{u,i_j}$

In any case, we can mostly precompute in advance.

# Utility Matrix

The matrix is sparse.

⇒ clustering ⇒ reduced matrix

# Utility Matrix

The matrix is sparse.

⇒ clustering ⇒ reduced matrix

Estimate on the reduced matrix, then take items and users as representative for the cluster.

# Amazon : Item-to-Item Collaborative Filtering

Observations :

Clustering is expensive, reduces quality

# Amazon : Item-to-Item Collaborative Filtering

Observations :

Dimension reduction reduces quality

# Amazon : Item-to-Item Collaborative Filtering

Observations :

Users interact with very few items

# Amazon : Item-to-Item Collaborative Filtering

Observations :

Rapid response desirable

# Amazon : Item-to-Item Collaborative Filtering

Scales independent of the number of users or of items

- Online
- Offline

G. Linden, B. Smith, J. York, *Amazon.com Recommendations: Item-to-Item Collaborative Filtering*, Internet Computing (7, 1), 22 Jan 2003.

# Amazon : Item-to-Item Collaborative Filtering

Offline (Precomputation)

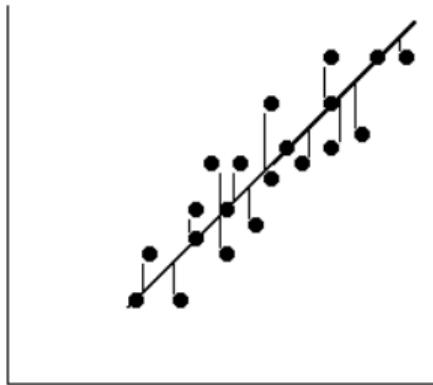
```
for each item  $I_1$  to sell do
    for each user  $C$  who has purchased  $I_1$  do
        for each item  $I_2$  bought by  $C$  do
             $(I_1, I_2)++$ 
        end
    end
    for each item  $I_2$  do
         $S_{I_1, I_2} \leftarrow S(I_1, I_2)$ 
    end
end
```

# Slope One

Linear regression on user opinions (ratings)

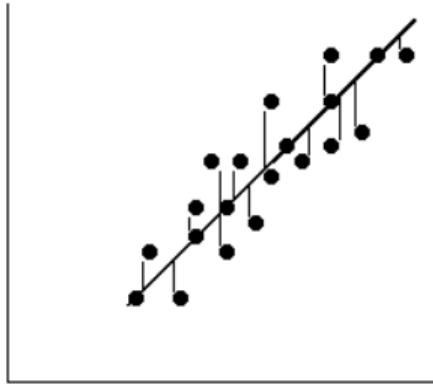
Daniel Lemire and Anna MacLachlan, *Slope One Predictors for Online Rating-Based Collaborative Filtering*, Proceedings of SIAM Data Mining (SDM) 2005.

# Slope One : Regression



<http://www.upa.pdx.edu/IOA/newsom/pa551/Image255.gif>

# Slope One : Regression



$$\min \sum (y_i - (ax_i + b))^2$$

<http://www.upa.pdx.edu/IOA/newsom/pa551/Image255.gif>

# Slope One : algorithm

Offline :

**for** chaque  $I_i, I_j$  **do**

$\mathcal{U} \leftarrow \{\text{users who have expressed an opinion on } I_i, I_j\}$

$\text{dev}_{i,j} \leftarrow \frac{1}{\|\mathcal{U}\|} \sum_{u \in \mathcal{U}} (r_u(i) - r_u(j))$

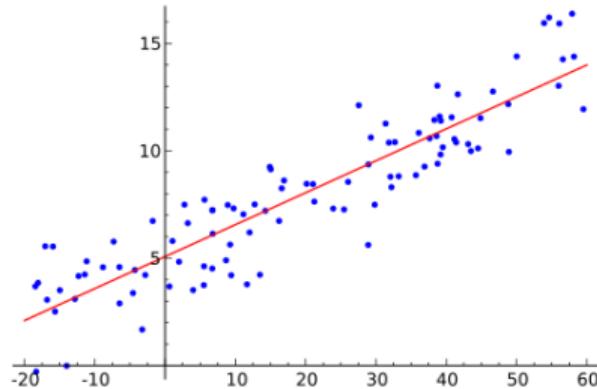
**end**

Online (for  $u$ ) :

$\mathcal{V} \leftarrow \{j \mid u \text{ has expressed an opinion on } I_j\}$

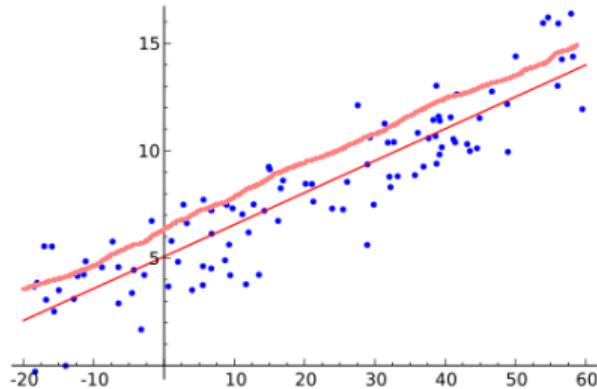
$r_u(i) \leftarrow \frac{1}{\|\mathcal{V}\|} \sum_{u \in \mathcal{V}} (\text{dev}_{i,j} - r_u(j))$

# Slope One : Regression



"Linear regression" by Sewa - Own work. Licensed under Public domain via Wikimedia Commons - [http://commons.wikimedia.org/wiki/File:Linear\\_regression.svg#mediaviewer/File:Linear\\_regression.svg](http://commons.wikimedia.org/wiki/File:Linear_regression.svg#mediaviewer/File:Linear_regression.svg)

# Slope One : Regression



# Dimensionality reduction

SVD, typically  $k = 20 \dots 100$

$$M = U\Sigma V^*$$

# Dimensionality reduction

SVD, typically  $k = 20 \dots 100$

$$(a_1 \quad \cdots \quad a_m) \begin{pmatrix} b_1 \\ \vdots \\ b_n \end{pmatrix} = \text{scalar}$$

# Dimensionality reduction

SVD, typically  $k = 20 \dots 100$

$$\begin{pmatrix} a_1 \\ \vdots \\ a_m \end{pmatrix} (b_1 \quad \cdots \quad b_n) = \begin{pmatrix} c_{1,1} & \cdots & c_{1,n} \\ \vdots & & \vdots \\ c_{m,1} & \cdots & c_{m,n} \end{pmatrix}$$

# Dimensionality reduction

SVD, typically  $k = 20 \dots 100$

$$\begin{pmatrix} a_{1,1} & a_{1,2} & a_{1,3} \\ \vdots & \vdots & \vdots \\ a_{m,1} & a_{m,2} & a_{m,3} \end{pmatrix} \begin{pmatrix} b_{1,1} & \cdots & b_{1,n} \\ b_{2,1} & \cdots & b_{2,n} \\ b_{3,1} & \cdots & b_{3,n} \end{pmatrix} = \begin{pmatrix} c_{1,1} & \cdots & c_{1,n} \\ \vdots & & \vdots \\ c_{m,1} & \cdots & c_{m,n} \end{pmatrix}$$

# Dimensionality reduction

SVD, typically  $k = 20 \dots 100$

$$\begin{pmatrix} a_{1,1} & \cdots & a_{1,k} \\ \vdots & & \vdots \\ a_{m,1} & \cdots & a_{m,k} \end{pmatrix} \begin{pmatrix} c_{1,1} & \cdots & c_{1,n} \\ \vdots & & \vdots \\ c_{k,1} & \cdots & c_{k,n} \end{pmatrix} = \begin{pmatrix} c_{1,1} & \cdots & c_{1,n} \\ \vdots & & \vdots \\ c_{m,1} & \cdots & c_{m,n} \end{pmatrix}$$

# Challenges

- How do we measure success?
- What are our features?

# Clustering

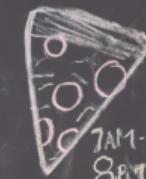
- kNN
- Curse of Dimensionality
- Scalability

# Clustering

- kNN  $k$ -Nearest Neighbor
- Curse of Dimensionality
- Scalability  $10^7$  clients,  $10^6$  objets

questions?

Todays  
Specials!



7AM-  
8PM

\$9.99

CREATE YOUR  
OWN PIZZA

CHICKEN MARSALA

\$11.99  
each

asparagus, soup or  
the day, mashed potato

# NLP

# Linear Programming

Maximize  $c^T x$   
subject to  $Ax \leq b$

# Summarising Text

- Abstractive (hard)
- Extractive (select sentences)

# Summarising Text

Challenge problem (cf. greedy solutions):

The cat is in the kitchen.

The cat drinks the milk.

The cat drinks the milk in the kitchen.

# Summarising Text

- Sentence selection
- Use n-grams
- Stemming
- Stop words
- Prune short sentences

*Dan Gillick, Benoit Favre, A Scalable Global Model for Summarization, 2009*

# Summarising Text

## Outline:

- ILP (*optimisation linéaire en nombres entiers*)
- Maximum coverage model

Dan Gillick, Benoit Favre, *A Scalable Global Model for Summarization*, 2009

# Summarising Text

ILP in canonical form:

$$\begin{aligned} & \text{Maximize } c^T x \\ & \text{subject to } Ax \leq b \\ & x \geq 0 \\ & x \in \mathbb{Z}^n \end{aligned}$$

*Dan Gillick, Benoit Favre, A Scalable Global Model for Summarization, 2009*

# Summarising Text

ILP in standard form:

$$\begin{aligned} & \text{Maximize } c^T x \\ & \text{subject to } Ax + s = b \\ & \quad s \geq 0 \\ & \quad x \in \mathbb{Z}^n \end{aligned}$$

*Dan Gillick, Benoit Favre, A Scalable Global Model for Summarization, 2009*

# Summarising Text

ILP in standard form:

$$\begin{aligned} & \text{Maximize } c^T x \\ & \text{subject to } Ax + s = b \\ & \quad s \geq 0 \\ & \quad x \in \mathbb{Z}^n \end{aligned}$$

This is NP hard.

*Dan Gillick, Benoit Favre, A Scalable Global Model for Summarization, 2009*

# Summarising Text

ILP in standard form:

$$\begin{aligned} & \text{Maximize } c^T x \\ & \text{subject to } Ax + s = b \\ & \quad s \geq 0 \\ & \quad x \in \mathbb{Z}^n \end{aligned}$$

Discussion: linear vs integer programming.

*Dan Gillick, Benoit Favre, A Scalable Global Model for Summarization, 2009*

# Summarising Text

Let

$c_i$  : presence of concept  $i$  in summary

$w_i$  : weight associated with  $c_i$

$l_i$  : length of sentence  $i$

$s_j$  : presence of sentence  $j$  in summary

$L$  : summary length limit

$Occ_{ij}$  : occurrence of  $c_i$  in  $s_j$

Dan Gillick, Benoit Favre, A Scalable Global Model for Summarization, 2009

# Summarising Text

## Summarisation

$$\begin{aligned} & \text{Maximize} \quad \sum_i w_i c_i \\ & \text{subject to} \quad \sum_j l_j s_j \leq L \\ & \quad s_j \text{Occ}_{ij} \leq c_i, \quad \forall i, j \\ & \quad \sum_j s_j \text{Occ}_{ij} \geq c_i \quad \forall i \\ & \quad c_j \in \{0, 1\}, \quad \forall i \\ & \quad s_j \in \{0, 1\}, \quad \forall j \end{aligned}$$

Dan Gillick, Benoit Favre, A Scalable Global Model for Summarization, 2009

Copyright 2017–2018 Jeff Abrahamson, for private use by course students only

ML Week

# Summarising Text

Notes:

- Selecting a sentence selects all concepts it contains
- Selecting a concept requires it be in at least one sentence
- $s_j \text{Occ}_{ij} \leq c_i, \forall i, j \Rightarrow$  no concept-less sentences

*Dan Gillick, Benoit Favre, A Scalable Global Model for Summarization, 2009*

# Sentiment Analysis

Many variations:

- Entire documents using computational linguistics
- Manually crafted lexicons

# Sentiment Analysis

## Techniques

- Template instantiation (requires domain knowledge)
- Passage extraction

# Sentiment Analysis

- Extract “opinion sentences” based on the presence of a predetermined list of product features and adjectives.
- Evaluate the sentences based on counts of positive vs negative polarity words (as determined by the Wordnet algorithm)

*Hu and Lieu, Mining and Summarizing Customer Reviews, 2004*

# Sentiment Analysis

- Extract “opinion sentences” based on the presence of a predetermined list of product features and adjectives.
  - “The food is excellent.”
  - “The food is an excellent example of how not to cook.”
- Evaluate the sentences based on counts of positive vs negative polarity words (as determined by the Wordnet algorithm)

*Hu and Lieu, Mining and Summarizing Customer Reviews, 2004*

# Sentiment Analysis

- Extract “opinion sentences” based on the presence of a predetermined list of product features and adjectives.
- Evaluate the sentences based on counts of positive vs negative polarity words (as determined by the Wordnet algorithm)

The good: fast, no training data, decent prediction.

The bad: fails on multiple word sense, non-adjectives; sensitive to context.

*Hu and Lieu, Mining and Summarizing Customer Reviews, 2004*

# Sentiment Analysis

Words aren't enough.

- “unpredictable plot” vs “unpredictable performance”

*Turney, Thumbs Up or Thumbs Down? Semantic Orientation Applied to Unsupervised Classification of Reviews, 2002*



questions?