1

FEATURE BASED RECOMMENDER SYSTEMS

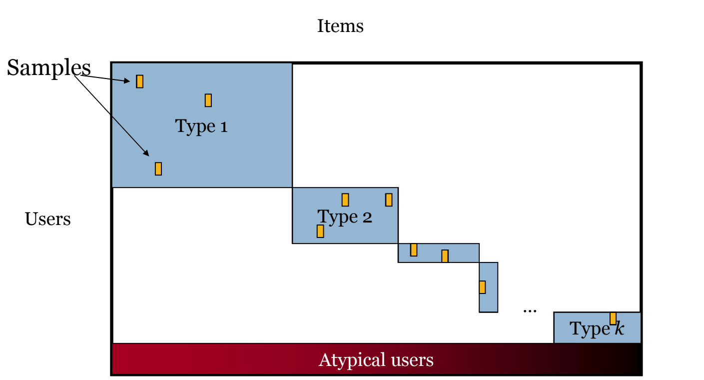
Mehrbod Sharifi
Language Technology Institute
Carnegie Mellon University

CF or Content Based?

2

- What data is available? (Amazon, Netflix, etc.)
  - Purchases/rental history or contents, reviews, etc.
  - Privacy issues? (Mooney `00 - Book RS)
- How complex is the domain?
  - Movies vs. Digital Products
  - Books vs. Hotels
- Generalization assumption holds?
  - Item-item similarity
  - User-user similarity

CF Assumption



Slide from Manning, et al. (Stanford Web Search and Mining Course '05)

What else can be done

4

- Use free available data (sometimes annotated) from user reviews, newsgroups, blogs, etc.
- Domains – roughly in the order they are studied
  - Products (especially Digital products)
  - Movies
  - Hotels
  - Restaurants
  - Politics
  - Books
- Anything where <u>choice</u> is involved

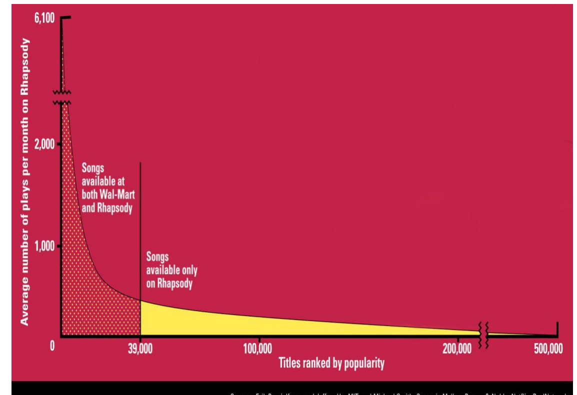
Some of the Challenges

5

- Volume → Summarization
  - Skew: More positives than negatives
- Subjectivity → Sentiment analysis
  - Digital camera photo quality
  - Fast paced movie
- Authority → ?
  - Owner, Manufacturer, etc.
  - Competitor, etc.

Product Offerings on web

6



Source: Chris Anderson (2004)

Number of Reviews

7

- newyork.citysearch.com (August 2006 crawl)
  - 17,843 Restaurants
  - 5,531 have reviews
  - 52,077 total number of reviews
  - Max: 242 reviews
- IMDB.com (March 2007 crawl)
  - 851,816 titles
  - 179,654 have reviews
  - 1,293,327 total number of reviews
  - Max: 3,353 reviews

Star Wars: Episode II - Attack of the Clones

Note: These stats are only based on my own crawl results.

Opinion Features vs. Entire Review

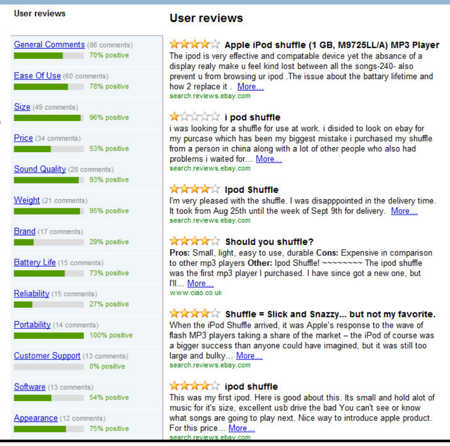
8

- General idea: Cognitive studies for text structures and memory (Bartlett, 1932)
- $Review = \sum_i feature_i$
- Feature rating vs. Overall rating
  - Car: durability vs. gas mileage
  - Hotel: room service vs. gym quality
- Features seem to specify the domain

Recommendation as Summarization

9

Feature-based



Examples – Restaurant Review

10

- Joanna's is overall a great restaurant with a **friendly** **staff** and **very tasty** **food**. The restaurant itself is **cozy** and **welcoming**. I dined there recently with a group of friends and we will all definitely go back. The **food** was **delicious** and we were **not kept waiting** long for our **orders**. We were seated in the charming garden in the back which provided a **great** **atmosphere** for chatter. I would highly recommend it.

Examples – Movie Review

11

- The **special effects** are **superb**--truly eye-popping and the action sequences are long, very fast and loads of fun. However, the **script** is **slow**, confusing and boring, the **dialogue** is **impossibly bad** and there's some **truly horrendous** **acting**.
- MacGregor is better because he is allowed to have a character instead of a totally dry cut-out like episode 1, <u>but it is still</u> a bit of an impression. Likewise Anakin is much better here (could he have been worse?) and Christensen tries hard – at first simmering with arrogance <u>but later</u> letting rage and frustration become his master for the first time; he is <u>still</u> a bit too wooden and a bland actor for me but at least he is <u>better than</u> Lloyd.

NL Challenges (Nigam '04)

12

- **Sarcasm:** it's great if you like dead batteries
- **Reference:** I'm searching for the best possible deal
- **Future:** The version coming out in May is going to rock
- **Conditions:** I may like the camera if the …
- **Attribution:** I think you will like it [but no one may like it!]

Another Example (Pang '02)

13

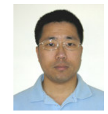
- This film <u>should be</u> **brilliant**. It <u>sounds like</u> a **great** plot, the actors are first grade, and the supporting cast is **good** as well, and Stallone is <u>attempting to</u> deliver a **good performance**. However, it can't hold up.

Paper 1 of 2

14

Mining and summarizing customer reviews

Minqing Hu



Bing Liu

SIGKDD 2004

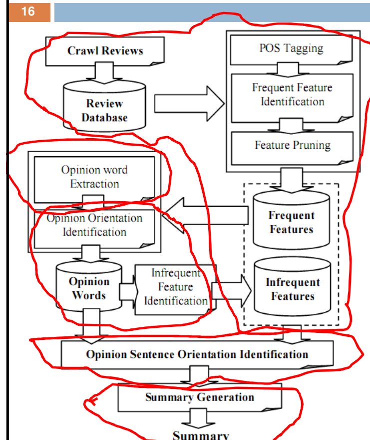
General outline of similar systems

15

1. Extract features e.g., scanner quality
2. Find opinion/polar phrases: opinion/polar word + feature
3. Determine sentiment orientation/polarity for **words**/phrases
4. Find opinion/subjective **sentences** : sentence that contain opinions
5. Determine sentiment **orientation**/polarity for sentence
6. Summarized and rank results

Hu and Liu: System Architecture

16



1. Product feature extraction
2. Identify opinion words
3. Opinion orientation at word level
4. Opinion orientation at sentence level
5. Summary

Step 1: Mining product features

17

- Only explicit features
  - Implicit: camera fits in the pocket nicely
- Association mining: Finds frequent word sets
- Compactness pruning: considering order of words based on frequency
- Redundancy pruning: eliminate subsets, e.g., battery life vs. life

Market Basket Analysis (Agrawal '93)

aka. support and confidence analysis, association rule mining

- "items" = $\{i_1, i_2, \ldots, i_m\}$
- "baskets" = $\{t_1, t_2, \ldots, t_n\}$.
- $t \subseteq I$
- $X, Y \subseteq I$, association rule: $X \rightarrow Y$
- {milk, bread} → {cereal}
- Support=#{milk, bread, cereal}/n
- Confidence=#{milk, bread, cereal}/# {milk, bread}
- Min Sup and Min Conf thresholds
- Apriori algorithm

Market Baskets for Text

- Baskets=Documents, Items=Words

doc1:	Student, Teach, School
doc2:	Student, School
doc3:	Teach, School, City, Game
doc4:	Baseball, Basketball
doc5:	Basketball, Player, Spectator
doc6:	Baseball, Coach, Game, Team
doc7:	Basketball, Team, City, Game

Step 2 &3: Opinion **word** and their sentiment orientation

20

- Only adjectives
- Start from a seed list and expand with WordNet only when necessary.

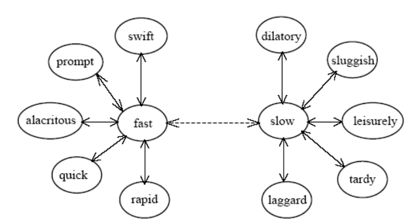


Figure 4: Bipolar adjective structure, (→ = similarity; ---> = antonymy)

Step 4: Sentence Level

21

- Opinion sentence has at least one opinion word and one feature, e.g., The strap is horrible and gets in the way of parts of camera you need to access.
- Attribute the opinion by **proximity** to the feature
- Summing up the positive and negative orientation of and consider negation. e.g., "but" or "not"
- Determining infrequent features: opinion word but no frequent feature → find closest noun phrase. Ranking step will de-emphasize irrelevant features in this step.

Data

22

- Amazon.com and Cnet.com
- 7 Products in 5 Classes
- 1621 Reviews
- Annotated for product features, opinion phrases, opinion sentences and the orientations.
- Only explicit feature

Example

GREAT Camera., Jun 3, 2004
Reviewer: **jprice174** from Atlanta, Ga.

I did a lot of research last year before I bought this camera... It kinda hurt to leave behind my beloved nikon 35mm SLR, but I was going to Italy, and I needed something smaller, and digital.

The pictures coming out of this camera are amazing. The 'auto' feature takes great pictures most of the time. And with digital, you're not wasting film if the picture doesn't come out.

…

Summary:

Feature1: picture

Positive: 12

- The pictures coming out of this camera are amazing.
- Overall this is a good camera with a really good picture clarity.

…

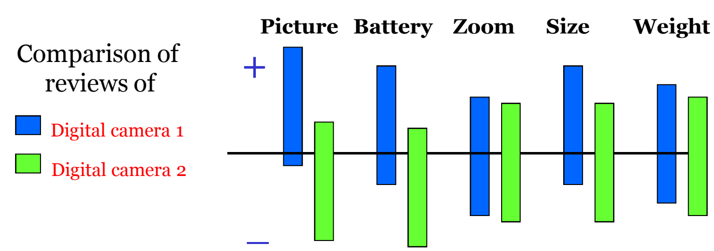
Negative: 2

- The pictures come out hazy if your hands shake even for a moment during the entire process of taking a picture.
- Focusing on a display rack about 20 feet away in a brightly lit room during day time, pictures produced by this camera were blurry and in a shade of orange.

Feature2: battery life

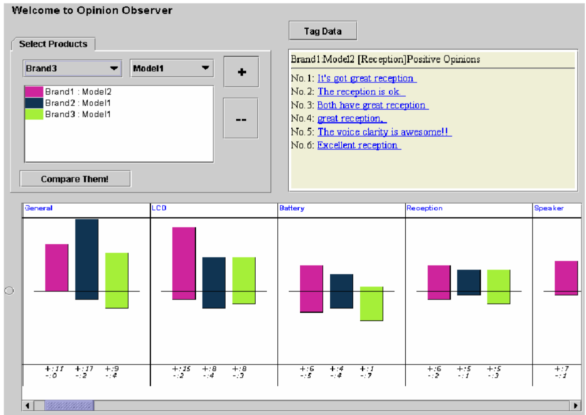
…

Visual Summarization & Comparison



Software Interface

25



Results – Feature Level

26

Table 1: Recall and precision at each step of feature generation

Product name	No. of manual features	Frequent features (association mining)		Compactness pruning		P-support pruning		Infrequent feature identification	
		Recall	Precision	Recall	Precision	Recall	Precision	Recall	Precision
Digital camera1	79	0.671	0.552	0.658	0.634	0.658	0.825	0.822	0.747
Digital camera2	96	0.594	0.594	0.594	0.679	0.594	0.781	0.792	0.710
Cellular phone	67	0.731	0.563	0.716	0.676	0.716	0.828	0.761	0.718
Mp3 player	57	0.652	0.573	0.652	0.683	0.652	0.754	0.818	0.692
DVD player	49	0.754	0.531	0.754	0.634	0.754	0.765	0.797	0.743
Average	**69**	**0.68**	**0.56**	**0.67**	**0.66**	**0.67**	**0.79**	**0.80**	**0.72**

Table 2: Recall and precision of FASTR

	Recall	Precision	No. terms
Digital camera1	0.1898	0.0313	479
Digital camera2	0.1875	0.0442	407
Cellular phone	0.1493	0.0275	364
Mp3 player	0.1403	0.0214	374
DVD player	0.1633	0.0305	262
Average	**0.1660**	**0.0309**	**377.2**

1. Too many terms and not all product features
2. No one-word terms

Results – Sentence Level

27

Table 3: Results of opinion sentence extraction and sentence orientation prediction

Product name	Opinion sentence extraction		Sentence orientation accuracy
	Recall	Precision	
Digital camera1	0.719	0.643	0.927
Digital camera2	0.634	0.554	0.946
Cellular phone	0.675	0.815	0.764
Mp3 player	0.784	0.589	0.842
DVD player	0.653	0.607	0.730
Average	**0.693**	**0.642**	**0.842**

Paper 2 of 2

28

Extracting Product Features and Opinions from Reviews

Ana-Maria Popescu   Oren Etzioni

EMNLP 2005

Popescu and Etzioni: System Architecture

29

Input: product class C, reviews R.
Output: set of [feature, ranked opinion list] tuples

R' ← parseReviews(R);
E ← findExplicitFeatures(R', C); ← Step 1
O ← findOpinions(R', E); ← Step 2-5
CO ← clusterOpinions(O);
I ← findImplicitFeatures(CO, E);
RO ← rankOpinions(CO);
$\{(f, o_i, ...o_j)...\}$ ← outputTuples(RO, I ∪ E);

Step 1: Extract Features

30

- OPINE: build based on KnowItAll, web-based IE system (creates extractions rule based on relations).
- Extract all products and properties recursively as features
- Feature Assessor: use PMI between feature, f and meronymy (part/whole or is-a) discriminator, d: e.g., "of scanner")

$$\mathrm{PMI}(f, d) = \frac{\mathrm{Hits}(d + f)}{\mathrm{Hits}(d) * \mathrm{Hits}(f)}$$

Feature Extraction Result

31

- Hu: Association Mining
- Hu+A/R: Hu and feature assessor (using review data only)
- Hu+A/R+W: Hu+A/R and Web PMI
- OP/R: OPINE extraction with feature assessor
- OPINE: OP/R + Web PMI

Data	Explicit Feature Extraction: Recall				
	Hu	Hu+A/R	Hu+A/R+W	OP/R	OPINE
D_1	*0.82*	-0.16	-0.08	-0.14	**-0.02**
D_2	*0.79*	-0.17	-0.09	-0.13	**-0.06**
D_3	*0.76*	-0.12	-0.08	-0.15	**-0.03**
D_4	*0.82*	-0.19	-0.04	-0.17	**-0.03**
D_5	*0.80*	-0.16	-0.06	-0.12	**-0.02**
Avg	*0.80*	-0.16	-0.07	-0.14	**-0.03**

Data	Explicit Feature Extraction: Precision				
	Hu	Hu+A/R	Hu+A/R+W	OP/R	OPINE
D_1	*0.75*	+0.05	+0.17	+0.07	**+0.19**
D_2	*0.71*	+0.03	+0.19	+0.08	**+0.22**
D_3	*0.72*	+0.03	+0.25	+0.09	**+0.23**
D_4	*0.69*	+0.06	+0.22	+0.08	**+0.25**
D_5	*0.74*	+0.08	+0.19	+0.04	**+0.21**
Avg	*0.72*	+0.06	+ 0.20	+0.07	**+0.22**

- 400 Hotel Reviews, 400 Scanner Reviews: 89% precision and 73% recall (where annotator agreed)

Step 2-5: Extracting Opinion Phrases

32

- 10 Extraction rules

Extraction Rules	**Examples**
if $\exists(M, NP = f) \rightarrow po = M$	(expensive) scanner
if $\exists(S = f, P, O) \rightarrow po = O$	lamp has (problems)
if $\exists(S, P, O = f) \rightarrow po = P$	I (hate) this scanner
if $\exists(S = f, P, O) \rightarrow po = P$	program(crashed)

- Using dependency parsing (instead of proximity – as input for next step)

Rule Templates	**Rules**
$dep(w, w')$	$m(w, w')$
$\exists v$ s.t. $dep(w, v), dep(v, w')$	$\exists v$ s.t. $m(w, v), o(v, w')$
$\exists v$ s.t. $dep(w, v), dep(w', v)$	$\exists v$ s.t. $m(w, v), o(w', v)$

- Potential opinion phrases will only be selected if they are labeled as positive or negative in the next step

Finding Semantic Orientation (SO)

33

- SO label: Negative, Positive, Neutral
- Word: w, Feature: f, Sentence: s
- Find SO for all w's
- Find SO for (w,f)'s given SO of w's
  - Hotel: "hot room" vs. "hot water"
- Find SO for each (w,f,s)'s given SO of (w,f)'s
  - Hotel: "large room"? Luxurious or Cold
- Using **relaxation labeling**

Relaxation Labeling (Hummel et al. '83)

34

- Iterative algorithm to assign <u>labels</u> to <u>objects</u> by optimizing some <u>support function</u> constrained by <u>neighborhood features</u>
- Objects, w: words
- Labels, L: {positive, negative, neutral}
- Update equation: $P(l(w) = L)_{(m+1)} = \frac{P(l(w) = L)_{(m)}(1 + \alpha q(w, L)_{(m)})}{\sum_{L'} P(l(w) = L')_{(m)}(1 + \alpha q(w, L')_{(m)})}$
- Support function: considers the word neighbors N by their label assignment A: $A_k = \{(w_j, L_j) | w_j \in N\}, 0 < k \leq 3^{|N|}$

$$q(w, L)_{(m)} = \sum^{3^{|N|}} P(l(w) = L | A_k)_{(m)} * P(A_k)_{(m)}$$

$$q(w, L)_{(m)} = \sum_{k=1}^{3^{|N|}} P(l(w) = L | A_k)_{(m)} * \prod_{j=1}^{|N|} P(l(w_j) = L_j)_{(m)}$$

Relaxation Labeling Cont.

35

- Relationship T (1..j) $P(l(w) = L | A_k)_{(m)} = P(l(w) = L | \bigcup A_{k,T})_{(m)}$
  - Conj. And Disjunction $P(l(w) = L | A_k)_{(m)} = \sigma(\sum_{i=1}^{j} f_i(w, L, A_{k,i})_{(m)} * c_i)$
  - Dependency rules $f_T(w, L, A_{k,T})_{(m)} = P(l(w) = L)_{(m)} * \prod_{j=1}^{|N_T|} P(L_j | l(w) = L)$
  - Morphological rules
  - WordNet: synonyms, antonyms, is-a
- Initialize with PMI $(P(l(w) = L)_{(0)})$

Results on SO

36

- PMI++: PMI of opinion phrase instead of just opinion word
- Hu++: considers POSs other than adjectives: nouns, adverb, etc. (still context independent)

Measure	PMI++	Hu++	OPINE
OP Extraction: Precision	0.71	+0.06	**+0.08**
OP Extraction: Recall	0.78	-0.08	**-0.02**
OP Polarity: Precision	0.80	-0.04	**+0.06**
OP Polarity: Recall	0.93	+0.07	**-0.04**

Type	PMI++		Hu++		OPINE	
	P	R	P	R	P	R
adj	0.73	0.91	+0.02	-0.17	**+0.07**	**-0.03**
nn	0.63	0.92	+0.04	-0.24	**+0.11**	**-0.08**
vb	0.71	0.88	+0.03	-0.12	**+0.01**	**-0.01**
adv	0.82	0.92	+0.02	-0.01	**+0.06**	**+0.01**
Avg	0.72	0.91	+0.03	-0.14	**+0.06**	**-0.03**

More recent work

37

- Focused on different parts of system, e.g., word polarity:
  - Contextual polarity (Wilson '06)
    - Extracting features from word contexts and then using boosting
  - SentiWordNet (Esuli '06)
    - Apply SVM and Naïve Bayes to WordNet (gloss and the relationships)

Thank You

38

Questions