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Mining E-commerce Data The Good, the Bad, and the Ugly

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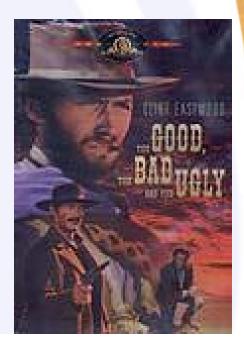
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- The Good
 E-commerce is the killer domain for data mining
- The Bad You need more than web logs and you must conflate many data sources
- The Ugly
 Pre-processing and post-processing are hard
- E-metrics
- Stories from mining real data "Peeling the onion"
- Summary

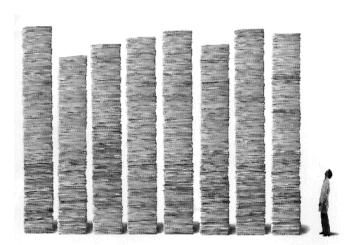


Successful data mining benefits from:

- ► Large amount of data (many records)

 If you sell five items an hour on average, you'll have about 1.8M clicks in the first month. Yahoo! has 1B clicks, or 10GB/hour
- Rich data with many attributes (wide records)
 With proper design, many attributes are available
- Clean data collection (avoid GIGO)
 Electronically collected, no legacy systems
- Actionable domain (have real-world impact Easy to change sites, ads, targeted campaigns, cross-sells
- Measurable return-on-investment

E-commerce has all the right ingredients



- Clickstreams generate huge amounts of data
- Yahoo! has 1 billion page views a day.
 Web log data for page views is 10GB per hour!
- New e-commerce sites, even if small, generate sufficient data for effective mining quickly If you sell five items an hour on average, that's

5 items * 24 hours * 30 days / 2% conversion * 9 clicks-in-session >

1.6 million page views



Effective site design can log many attributes about what was shown or purchased:

- Product and product attributes
- Assortment attributes (when multiple products are shown)
- Promotions shown
- Visit attributes (e.g., visit count)
- Customer attributes (when known through login/registration)

- Collect data directly at webstore No legacy systems
- Collect what is needed by design Not as an afterthought
- Collect electronically reliable data
 No humans typing survey data from forms
- Sample at the right granularity level Architecture design principle: sample at the customer or session level, never at page view level



A bank discovered that almost 5% of their customers were born on the exact same date

Can you explain?

- Few data mining discoveries had a real impact on businesses.
 - Taking action requires changing complex systems, procedures, and human habits HARD in general Easier in the electronics world
- In e-commerce, many discoveries can be made actionable by
 - Changing web sites (e.g., personalization)
 - Targeted campaigns
 - Changing advertising strategies based on ROI
- Easy to offer cross-sells or up-sells Contrast with changing actual store layouts

Measure ROI



In e-commerce, it is easy to evaluate metrics, unlike in brick-and-mortar stores.

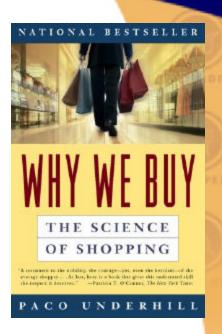
See Why We Buy: the Science of Shopping by Paco Underhill

In e-commerce it is easy to measure the effect of changes.

One can easily set control groups on a web site



The web is an experimental laboratory It is easy to change and measure the effect



One of our customers, Gymboree, sent e-mail campaign based on analysis of website data of registered users: 7 email designs to 4 segments

Results:

Segment 1 Segment 2 Segment 3



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- Very high clickthrough rate of 22% (normal is 10%)
- Average order size was 36% higher than normal
- Email with two age groups of the same gender outperformed that with single age

(medium targeting)

Lifestyle images better than products



Firms need web intelligence, not log analysis
-- Forrester Report, Nov 1999

Web logs provide little data, even in the Extended Common Log Format (ECLF)

Host

The Bad

- Time
- Request, e.g., an html page
- Referrer
- User agent (browser identifier)
- IP address
- Cookie
- Bytes, status, ...

What is on the Web Page?

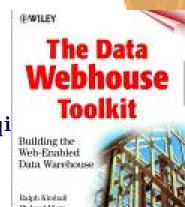


- Weblogs designed for analyzing web servers, not for mining e-commerce transactions and clickstreams
- Given a URL, what was displayed?
 - Reverse URL mapping. Very brittle.

http://www.amazon.com/exec/obi dos/ASIN 41580/105-9856660-9155942

is The Data WebHouse Toolkit

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Hard to derive attributes of the product, such as soft cover, author, edition, year?

Dynamic Content is Harder



- **The same URL will display different items**
- URLs are amazingly long in dynamic sites and information is in the application server session:

http://www.im.aa.com/American?BV_EngineID=dealikcjfekgbfdmcflmcfkhdgfh.7 &BV_Operation=Dyn_RawSmartLink&BV_SessionID=%40%40%40%4008226 17159.0968100982%40%40%40%40%40%form%25destination=index-member.tmpl&BV_ServiceName=American

 Personalized content (e.g., recommended cross-sell) is practically impossible to reconstruct from web logs

- HTTP is stateless
- Sessionizing is still a research topic

See Measuring the Accuracy of Sessionizers for Web Usage Analysis Berent, Mobasher, Spiliopoulou, and Wiltshire, in Proceedings of the Web Mining Workshop at the First SIAM International Conference on Data Mining, 2001

- Recreating user sessions is heuristic based:
 - IP addresses
 - Cookies
 - Browser type

Some events cannot be determined from weblogs:

 Add to shopping cart - needed to compute value of abandoned shopping carts

- Change quantity of item in cart
- Promotion offered on page
- Out of stock shown on the page
- Form information
- Search common keywords or keywords that were not found (an important warning to an e-commerce site)



- On one of our sport-related sites, the top searched keywords were:
 - Baseball
 - Video
 - Softball
 - Volleyball
 - Pins
 - Equestrian
 - Videos
 - Posters
 - Music
 - Poster

What is common to the words in red?

- On one of our sports-related sites, the top searched keywords (in order) were:
 - Baseball
 - Video
 - Softball
 - Volleyball
 - Pins
 - Equestrian
 - Videos
 - Posters
 - Music
 - Poster

Searches for red words yielded zero results!

- Some words just need a synonym
- Some words should send a strong message about items the store should carry!

Weblogs do not typically contain sufficient information to extract failed searches.

This isn't fancy analytics, but it's crucial.

About 11% of searches fail

Matching Web Logs to DB

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- Given a request, how do you
 - Match it to the customer in your database that filled a registration form?
 - **○** Determine if this is the customer's second visit or the 100th visit?
 - Determine if the customer previously purchased?
- These common requests are very hard to implement as an afterthought
- They are even harder when you try to find "scenarios" that match multiple events

Using hits and page views to judge site success is like evaluating a musical performance by its volume -- Forrester Report, 1999

- Most often-requested measures relate to conversion rates (buyers to browsers)
- Especially useful by referrer (e.g., ad)
- Given an HTTP request that has one of your ads as the referrer field, how can you tell if it resulted in a sale?

The KDD Cup 2000 data shows the following in their initial rampup period

Referrer	# Sessions	% of traffic	# Sales	Conv rate
ShopNow	16,178	6.9%	6	0.04%
FashionMall	19,685	8.4%	17	0.09%
MyCoupons	2,052	0.9%	170	8.28%

- Conversion rates differ by a factor of over 200!
- Knowing the likelihood of purchase dramatically changes the message to present

"Bad" Is Not So Bad

- Ignore web logs They are at the wrong granularity level to be useful
- Log the information yourself at the application layer
- The application knows what is on the page
 - The app controls sessions
 - The app can log business events
 - The app can tie a visitor to their customer information upon login
- Also see Structure and Content Preprocessing by Rob Cooley for more information



- Crawlers
- Handling large amounts of data
- Data transformations for analysis
- Marketing-level insight
- These are excellent research topics



- Search crawlers
- Shopping bots

Crawlers

- IE5 offline viewer
- **E-mail harvesters Evil**
- Students learning Perl scripts
- For understanding your customers, it is very important to filter out crawlers
- 30% of sessions come from bots/crawlers (most are measure of service bots such as Keynote)

Good

Fairly hard problem
 Some try to hide themselves

- Browsers identify themselves on every request in a field called *Useragent*
- Which useragents are bots?

```
Mozilla/4.75 [en] (WinNT; U)
Mozilla/4.0 (compatible; MSIE 5.5; Windows NT 4.0)
Mozilla/3.01 [en] (Win95; I)
Mozilla/4.0 (compatible; MSIE 5.0; Windows 98; DigExt; MSIECrawler)
Googlebot/2.1 (+http://www.googlebot.com/bot.html)
Mozilla/4.0 (compatible; MSIE 5.0; Win32)
```

All but the top two

- Criteria
 - Known robot user agents
 - User agents which never log in/never purchase
 - User agents with only 1-click or more than 100-click sessions
 - User agents with no referrer on all requests

 80% of the time spent in data analysis is typically spent transforming data

- What can be done today:
 - Automate transfer of data from webstore environment to data warehouse
 - Provide data transformation UI
 - Provided "canned" transformations for common business problems
- Business users without "data" or "analyst" in their title cannot spend the time to learn how to transform data

- Everything is a GO!
 - You collected data correctly
 - You built a data warehouse
 - You transformed the data
 - You ran a simple Perceptron (1-layer) neural network that predicts the target well



- The business user asks:
 - What does the 237-dimensional hyperplane represent?
- Insight must be comprehensible to biz users
 Sometimes required for legal reasons
 (e.g., no discrimination)

- Goal: Identify commonalities and differences across sites
- Data collected over the Christmas 2000 period
- Five e-commerce web sites running Blue Martini's software
- Both US (three sites) and Europe (two sites)
- Removed bots/crawlers

E-Metrics

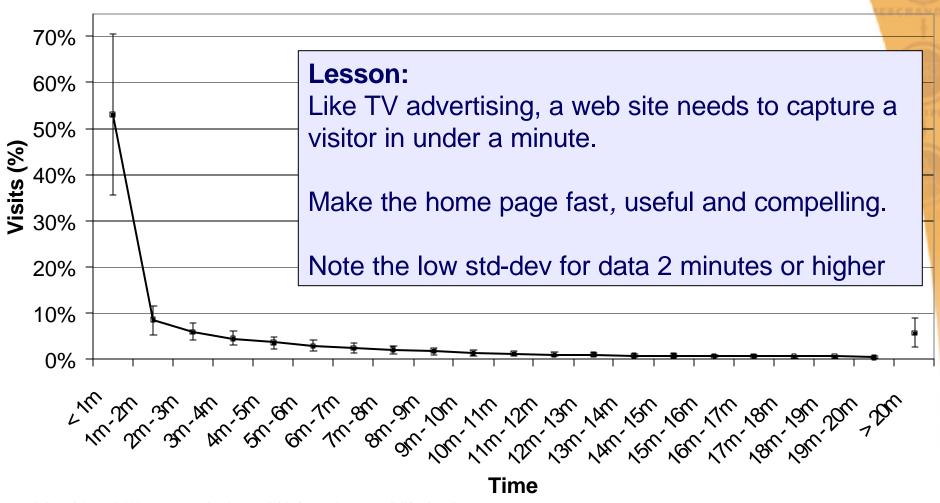
 Study available at <u>developer.bluemartini.com</u> under Data Mining and Analytics articles

- An average visitor
 - Views 8-10 pages
 - Spends 5 minutes on the site
 - Spends 35 seconds between pages
- An average purchasing visitor
 - Views 50 pages
 - Spends 30 minutes on the site
- These numbers are *Extremely* consistent across all of the sites in the study.

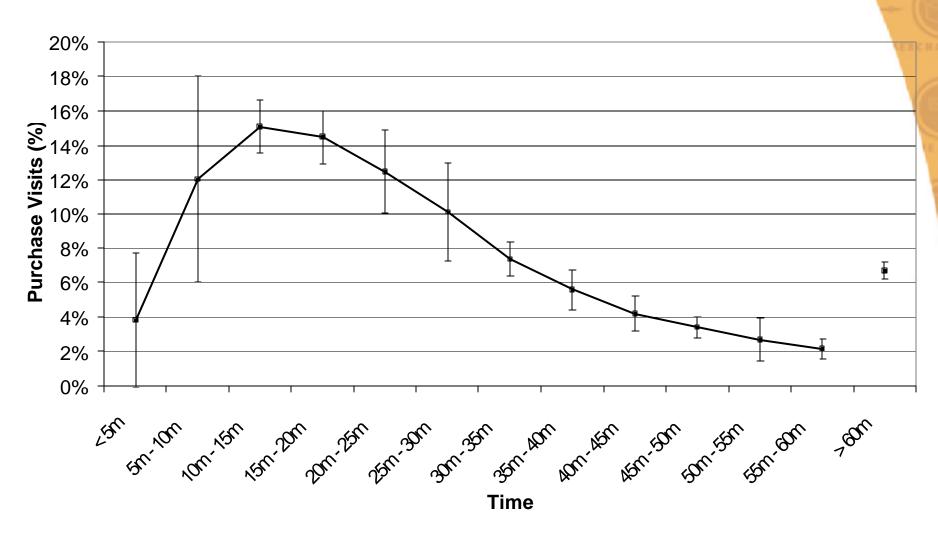
Visit Duration - Time



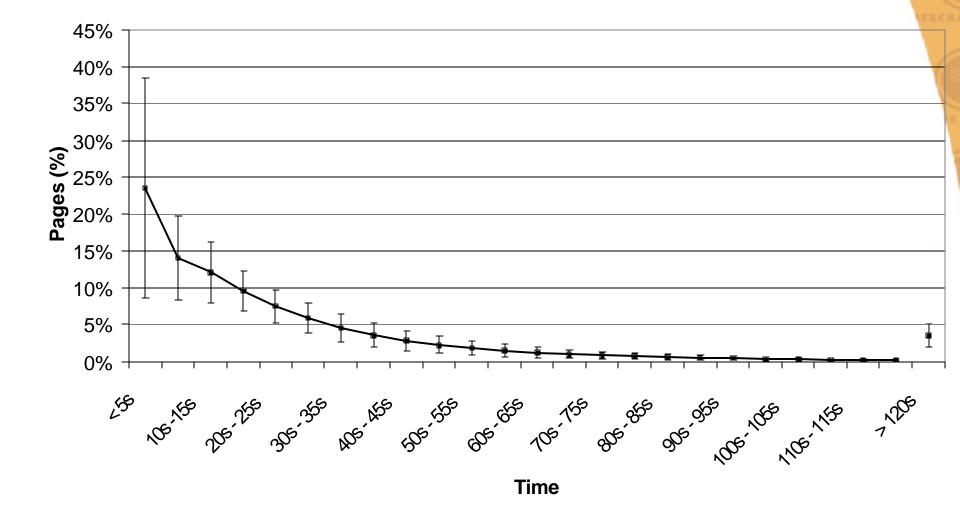
Average Visit Duration (Time)



Average Visit Duration (Time) - Purchase Visits



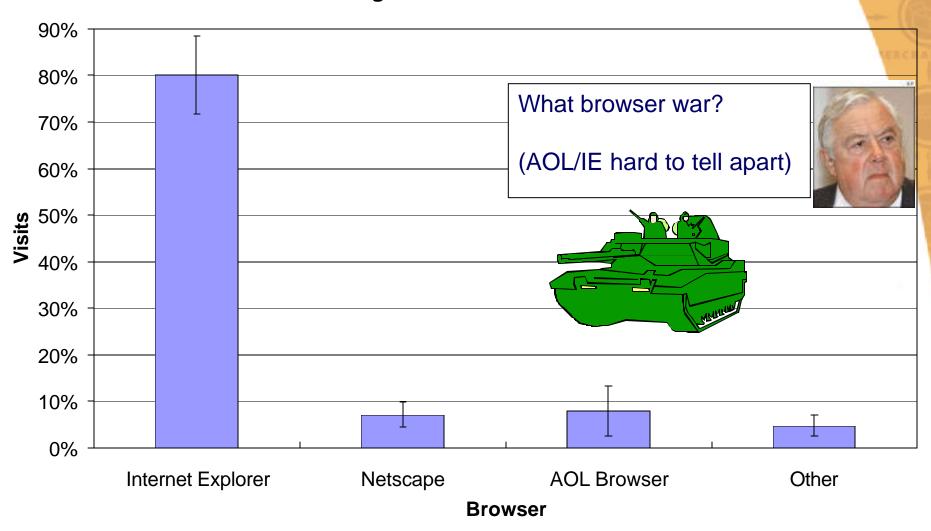
Average Think Time



Browser Distribution

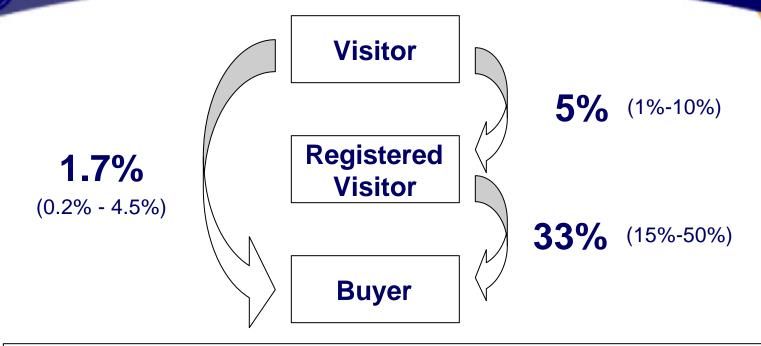


Average Browser Distribution



Conversion Rates





Lesson:

Few visitors bother to register.

Make it easy, fast and give incentives.

Lesson:

Many people who bother to register don't purchase. You know who they are, so you can target them.

Shopping cart abandonment rate34% (15% - 50%)

Lesson:

You know what they want, and sometimes know who they are. You can target them.

Search

6% of visits use search (1%-10%) 10% of searches fail to find any results

Lesson:

You can find out what they were looking for. You can correct the problem.

PLEASE

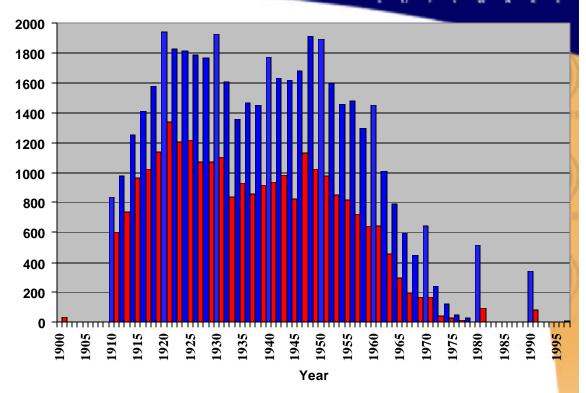
- 92% of Americans are concerned (67% very concerned) about the misuse of their personal information on the Internet.
 - FTC Report, May 2000
- 86% of executives don't know how many customers view their privacy policies.
 - Forrester Report, November 2000
- Q: What percentage of visitors read the privacy statement?
- A: Less than 0.3%

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The KDD CUP 98 data contained anomalies for date of birth [Georges and Milley, SIGKDD Explorations 2000]



- Spikes on years ending in zero (white dots on blue)
- Few individuals born prior to 1910
- Many more individuals who were born on even years (blue) as on odd years (red)

Why?

- A site has gender on the registration form
- Acxiom, a syndicated data provider, also provides gender
- A very large discrepancy found between
 - Males according to registration form and
 - Acxiom provided data

Why?

Hint: Acxiom only conflicted with females, claiming some females are males.

Never in the other direction



Teaser - Low Conversion Rates



 Recall that Conversion Rate is the ratio of buyers to browsers.

- High conversion rates are desired
- Reports showed some products have really low conversion rates?

Why?

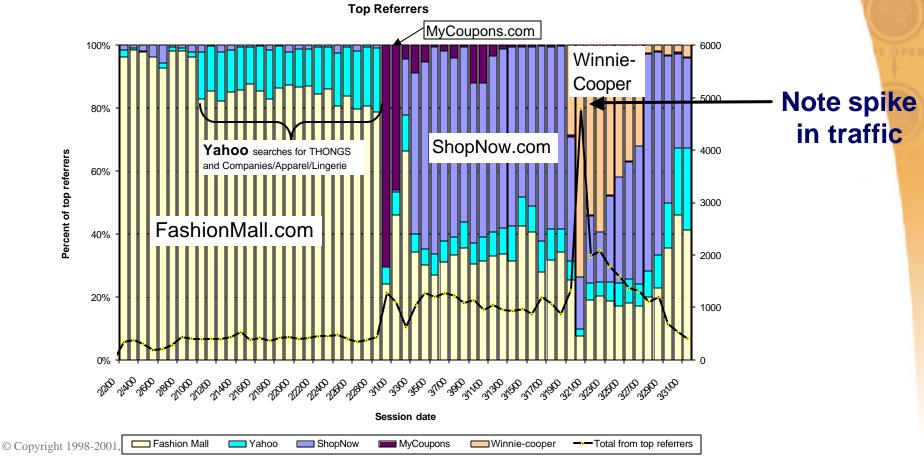


- Product Conversion Rate is the ratio of product purchases to product views
- High can conversion rates be over 100%

Teaser - Who is Winnie?



Referring site traffic for Gazelle.com, a leg-wear and leg-care web retailer. From KDD Cup 2000 Who is Winnie Cooper? What can you do about it?



Answer to Teaser



- Winnie-cooper is a 31 year old guy who wears pantyhose
- He has a pantyhose site
- 8,700 visitors came from his site in a few days (!)
- Actions:
 - Make him a celebrity and interview him about how hard it is for a men to buy pantyhose in stores
 - Personalize for XL sizes





- KDNuggets, Software for Web Mining http://www.kdnuggets.com/software/web.html
- WEBKDD Workshops in Web Mining http://robotics.Stanford.EDU/~ronnyk/WEBKDD2000/index.html http://robotics.Stanford.EDU/~ronnyk/WEBKDD2001/index.html
- WEB Mining Tutorials

 - Web Mining for E-Commerce, Jaideep Srivastava,
 The Fifth Pacific Asia Conference on Knowledge Discovery and Data Mining, 2001

Resources (II)

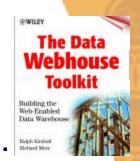


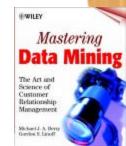
- The Data Webhouse Toolkit: Building the Web-Enabled Data Warehouse by Ralph Kimball, Richard Merz. ISBN: 0471376809 (Jan 2000)
- Mastering Data Mining: The Art and Science of Customer Relationship Management by Michael J. Berry, Gordon Linoff. ISBN: 0471331236
- The Data Mining and Knowledge Discovery special issue on Application of Data Mining to Electronic Commerce (volume 5, 1/2) January/April 2001. Special issue:

http://www.wkap.nl/issuetoc.htm/1384-5810+5+1/2+2001

Book ISBN: 0792373030

http://www.amazon.com/exec/obidos/ASIN/0792373030





- Web Mining Research: A Survey http://www.acm.org/sigs/sigkdd/explorations/issue2-1/contents.htm#Kosala
- Web Data Mining course at DePaul University by Bamshad Mobasher http://maya.cs.depaul.edu/~classes/cs589/lecture.html
- Integrating E-commerce and Data Mining: Architecture and Challenges, WEBKDD'2000 http://robotics.Stanford.EDU/~ronnyk/ronnyk-bib.html
- Drinking from the Firehose: Converting Raw Web Traffic and E-Commerce Data Streams for Data Mining and Marketing Analysis by Rob Cooley http://www.webusagemining.com/sys-tmpl/webdataminingworkshop/

- An Ideal E-Commerce Architecture for Building Web Sites Supporting Analysis and Personalization http://robotics.Stanford.EDU/~ronnyk/ronnyk-bib.html
- Analyzing Web Site Traffic, Sane Solutions http://www.sane.com/products/NetTracker/whitepaper.pdf
- Web Mining, Accrue Software http://www.accrue.com/forms/webmining.html

- Direct effect of web on established retailers may not be large, but lessons learned will affect other channels, so additional ROI comes from improvements to other channels
- The webstore provides an experimental laboratory and a trend-discovery system
 - Which cross-sells work?
 - Which ads are effective?
 - What are people looking for (failed searches for pokédex)

- Good: E-commerce is the killer-domain for data mining with all the right ingredients
- Bad: Good data collection is hard
 - Web logs are information poor
 - New sites should log clickstream and events in the app
- Ugly:
 - Data transformations take longer than you expect.
 - ➤ You must "peel the onion" for interesting insight See KDD CUP 2000 at http://www.ecn.purdue.edu/KDDCUP



Take Home Messages (III)



Always involve the business user

Many "interesting" discoveries turn out to be a result of

some intentional activity. "Peel the onion."

- Business users want simple, comprehensible results
 - Reports are not glamorous but most often needed
 - Simple algorithms are most useful especially if coupled with good visualizations
- The web is a measurement and experiments lab
 - Half the discoveries will carry over to the "real world"

- Many thanks to the data mining team members at Blue Martini Software
- Special thanks to Llew, Zijian, Brian, and Eric, who worked on the e-metrics project
- A copy of this talk is available at www.kohavi.com
- The reference for the talk/paper is

 Ron Kohavi. Mining e-commerce data: The good, the bad, and the ugly. In Foster Provost and Ramakrishnan Srikant, editors, Proceedings of the Seventh ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, August 2001. http://robotics.Stanford.EDU/users/ronnyk/goodBadUglyKDDItrack.pdf