

Technology Labs

Research Directions in Enterprise Knowledge Management

Rayid Ghani

Enterprise Search Today





Advanced Search

Accenture Technology Labs

SIT - Technology > Accenture Technology Labs Accenture Technology Labs Asset Monitoring & Optimization Practice Accenture Technology Labs Asset Monitoring & Optimization

https://kx.accenture.com/Organizations/Pages/AccentureTechnologyLabs.aspx

Content Current Date - 6/14/2005

Last Index Date - 2/13/2007 [View duplicates]

Accenture Technology Labs Patent Profiles

Accenture Technology Labs Patent Profiles Accenture Technology Labs Patent Profiles Accenture Technology Labs

https://kx.accenture.com/TechMeth/Pages/LabsPatent-AllProfiles.aspx

Content Current Date - 4/7/2005

Last Index Date - 12/29/2006 [View duplicates]

Accenture Technology Labs: Contacts - Meet the Labs

Accenture Technology Labs: Accenture Technology Labs falls under Systems Integration & Technology under the direction of the director of the Accenture Technology Labs. responsible for setting strategic direction and managing

https://kx.accenture.com/Organizations/Pages/AccentureTechnologyLabs-Contacts.aspx

Content Current Date - 5/24/2005

Last Index Date - 7/6/2007

Accenture Technology Labs - Sell & Deliver

paper describing Accenture Technology Labs' "Command and Control (C2) Interactive Wall" and how it Short Video Clips of Technology Prototypes and Solutions from Accenture Technology Labs showcasing the Accenture Technology Labs latest prototypes and solutions.

https://kx.accenture.com/Organizations/Pages/AccentureTechnologyLabs-SellDeliver.aspx

Content Current Date - 6/13/2005

Last Index Date - 12/29/2006

Accenture Technology Labs India

SIT - Technology - Accenture Technology Labs Accenture Technology Labs India in Collaboration - Accenture Technology Labs creates a Virtual Corridor between Accenture offices i

https://kx.accenture.com/Organizations/Pages/AccentureTechnologyLabs-Bangalore.aspx

Content Current Date - 3/20/2006

Last Index Date - 6/28/2007

Accenture Technology Labs - About the Organization

SIT - Technology > Accenture Technology Labs Accenture Technology Labs, the technology research and development (R&D) organization within Acce Accenture Technology Labs falls under Systems Integration & Technology under the direction of the

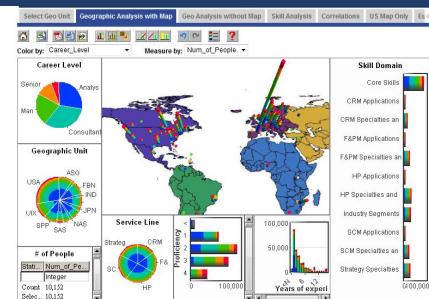
https://kx.accenture.com/Organizations/Pages/AccentureTechnologyLabs-About.aspx

Enterprise IR is different from Web IR

- Scale
- Hyperlinks
- Static ranking
- Structured data
- Version Control
- Expectations (THE document vs a document)
- Redundancy
- Security/access control
- Users (roles/needs/context)
- Tasks (Business processes)

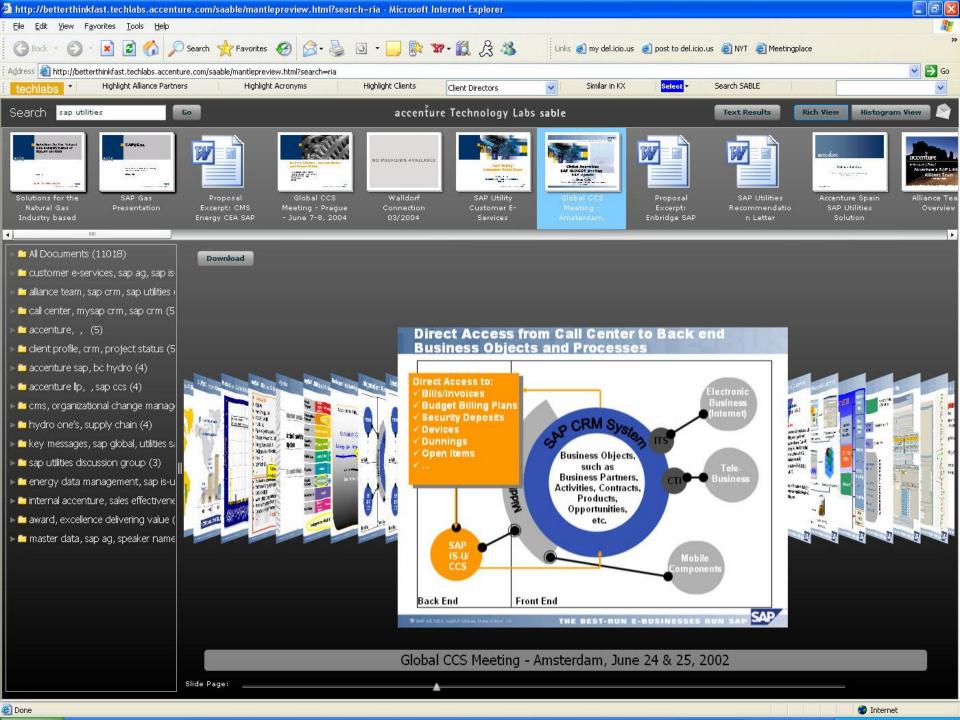
Enterprise Tasks involve specialized business processes and roles

- Proposal Writing
- Marketing
- Selling/Estimation
- Risk management
- Requirements Analysis
- Software Testing
- Training/Learning
- Outsourcing
- Vendor evaluation
- Procurement
- Business Intelligence
- Project Staffing
- Recruiting



Collaborative Document Development Process

- Identify requirements
- Identify collaborators/team
- Develop high level themes
- Create outline with sections
- Assign sections to individuals
- Support individuals finding content to complete sections
- Support checkpoints and alerts
- Consolidate drafts of sections and provide support to ensure consistency, compliance, theme integration, tracking changes
- Consolidate to produce final document
- Review for consistency, compliance, integration
- finalize



Areas of Improvement

Access to specific content instead of large monolithic documents

Task and Contextsensitive access to knowledge

Enterprise KM

Document Analysis and Review Tools

Process-based Support

Areas of Improvement

Task and Context-Access to specific content instead of large sensitive access to monolithic documents knowledge Enterprise KM **Document Analysis and** Process-based Support Review Tools

From monolithic documents to reusable pieces of information

- Entities (experts for example <u>demo</u>)
- Document Chunking (<u>demo</u>)
- Images (<u>demo</u>)

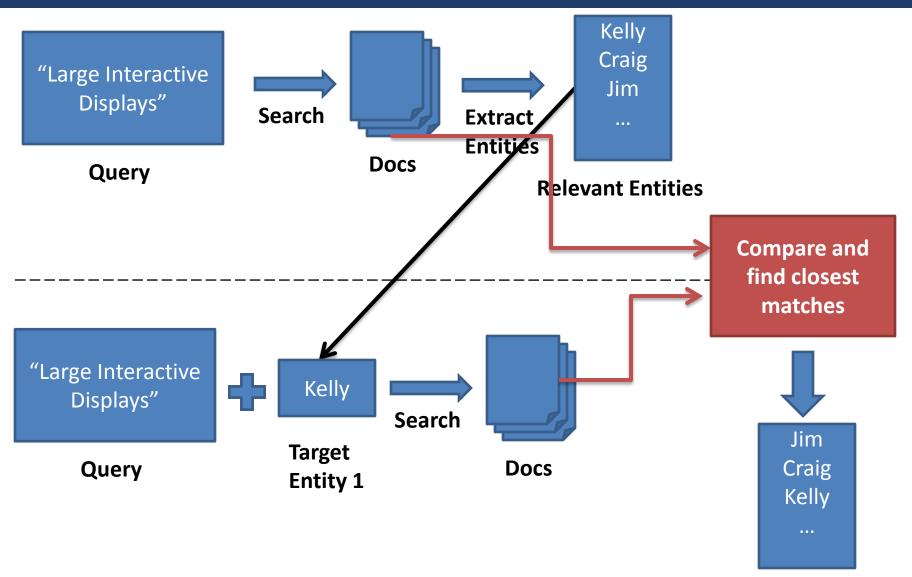
Motivating business task

Task: Developing a consulting project proposal

- Information Needs
 - People that have worked on similar proposals
 - Clients for which Accenture has done similar work
 - Vendors that Accenture has used for similar work
 - Alliances Accenture has with companies that we can partner with
 - People available to work on the project

— ...

Entity Retrieval & Ranking



Ranked List of Relevant Entities

Online experiments

Expert Search as an extension to enterprise

search



IM bot to find and interact with experts

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Labelland

Commission Cysteric Send to

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Document Chunking



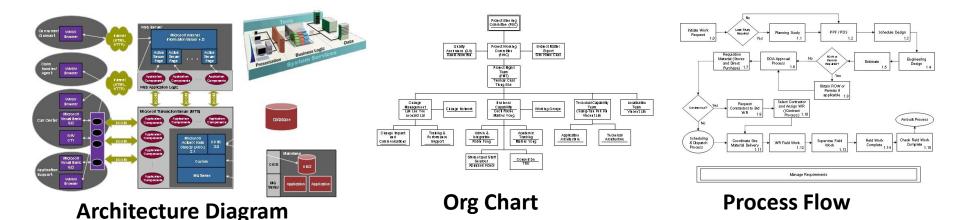
•Approach:

Determine boundary of sections by segmenting documents Use clustering to find similar sections Classify sections into predetermined section classes

•Output:

List of labeled individual sections from the document

Enterprise Image Classification and Retrieval

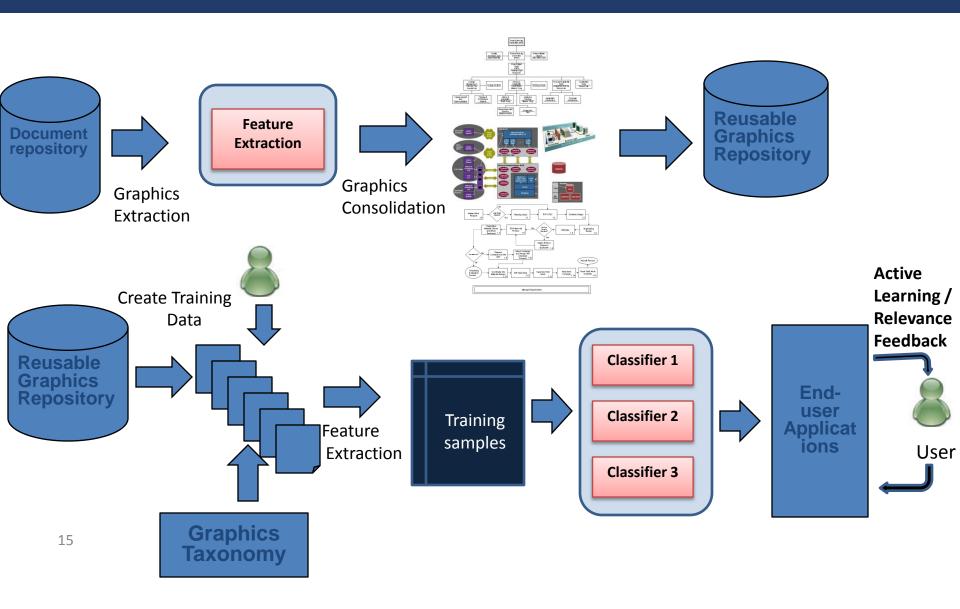


<u>Demo</u>

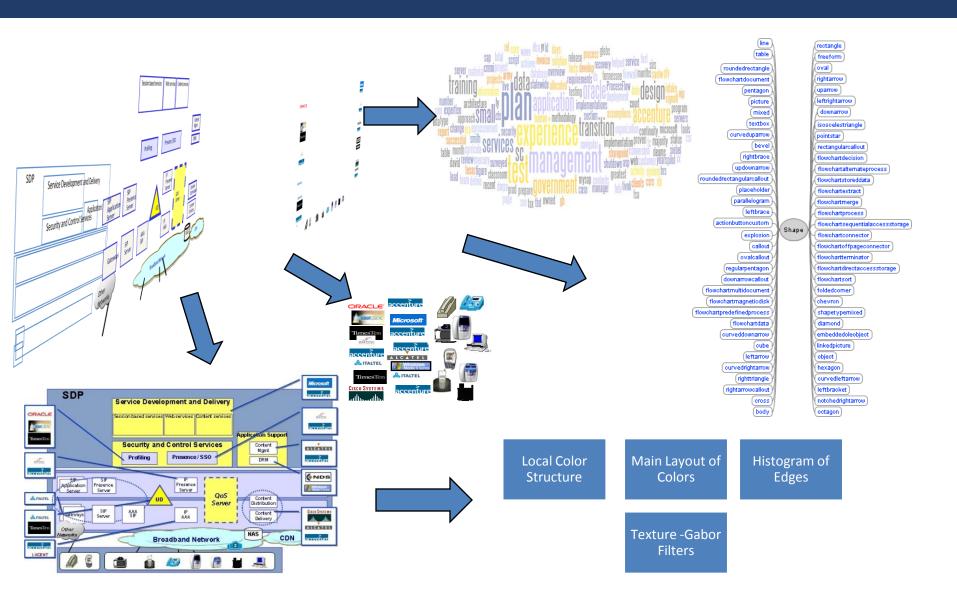
Approach

- Image extraction from office Documents
- Supervised learning (6-10 categories) with structural, visual, and text features of the image
- Index image using words and image category

Overview of Approach



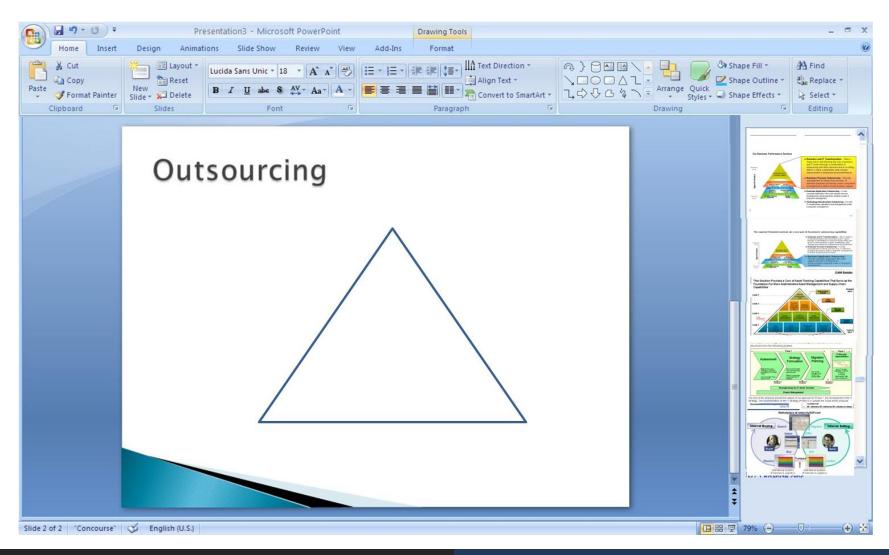
Feature Extraction



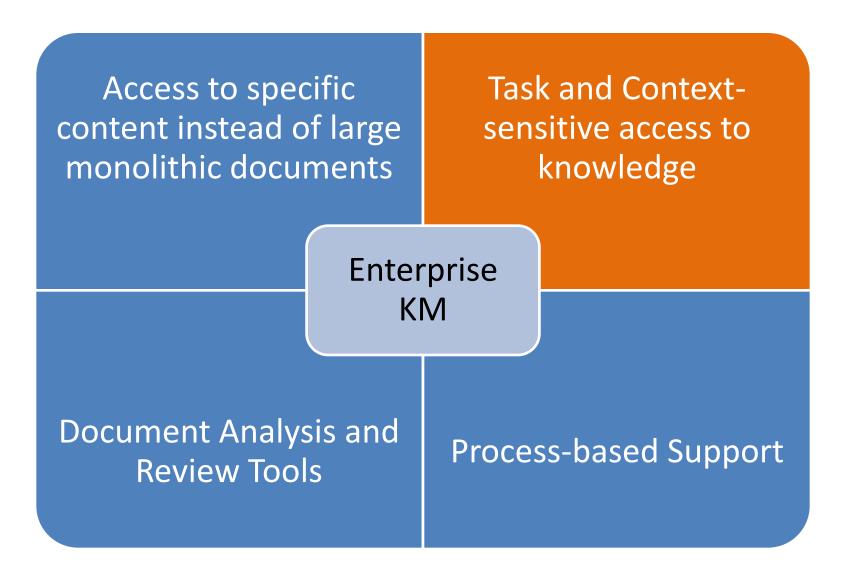
Task specific application



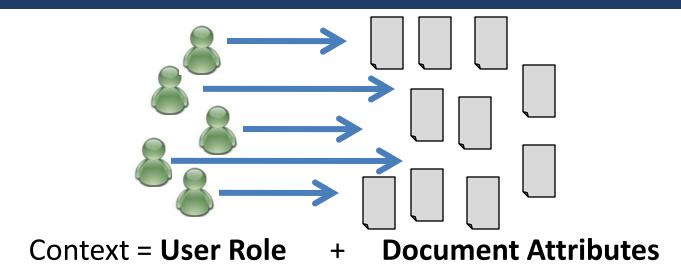
3. Task specific application



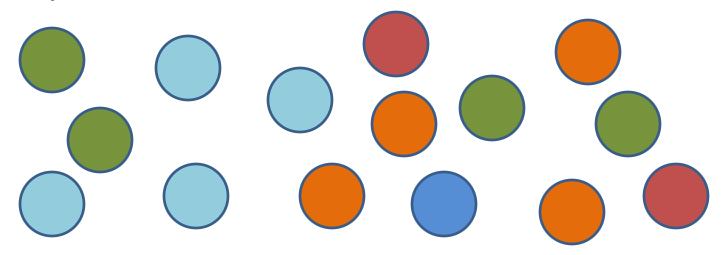
Areas of Improvement



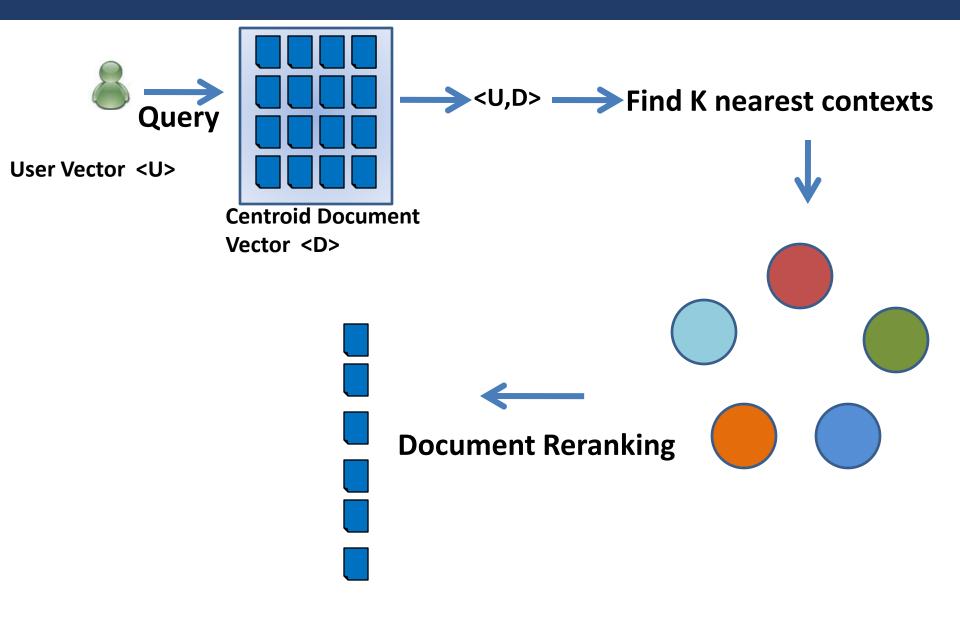
Context



Super Contexts = Cluster All contexts over time



Context-sensitive ranking



Contextual Access to Information

 Current search engines are based on keywords and do not work well with long (sentence-like) queries

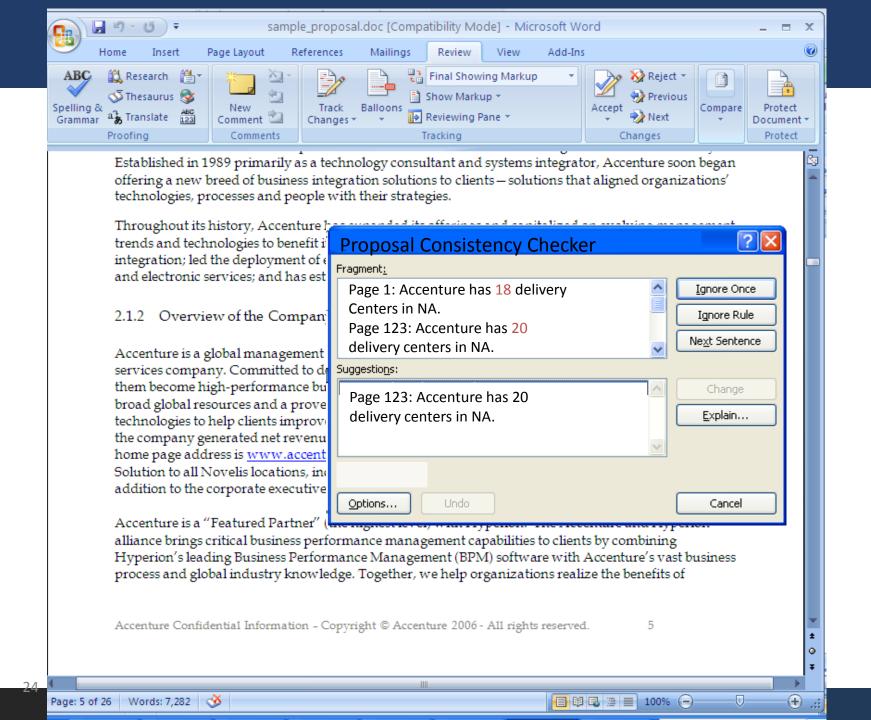
Need

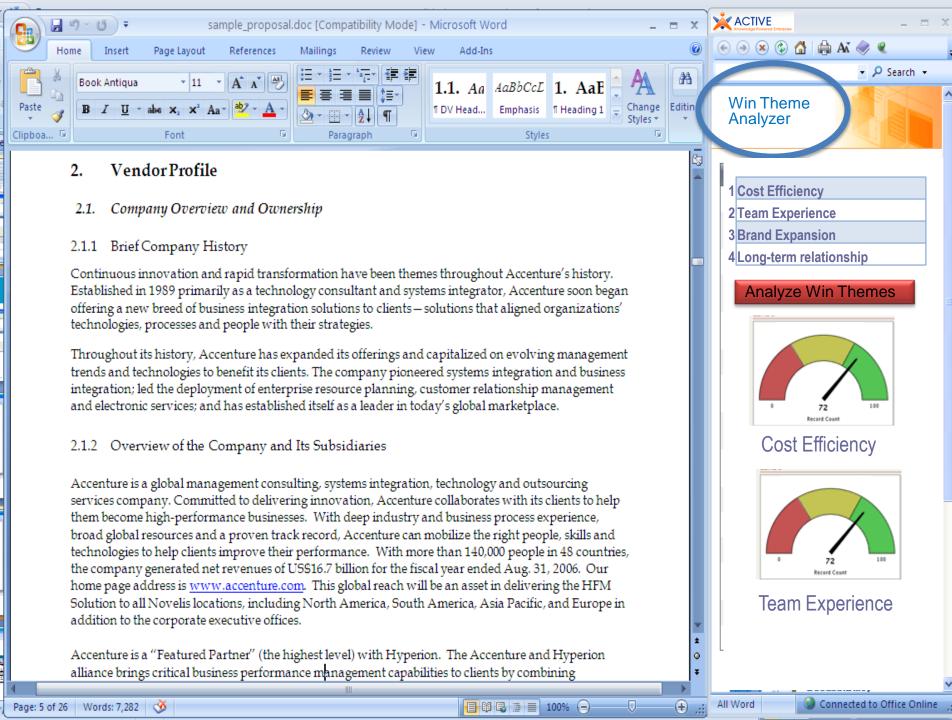
We are writing a response to a proposal for an online retailer that is exploring new marketing capabilities to improve their customer and marketing results through direct mail, email, DE USE web and outbound telemarketing programs. The focus is on differe flexible delivery of an end-to-end CRM solution, as well as alternate delivery methods that could appeal to the client. **EXAM**: The proposed end-to-end option will leverage our alliances with Acxiom, Unica and Teradata

Long Query (prototype demo)

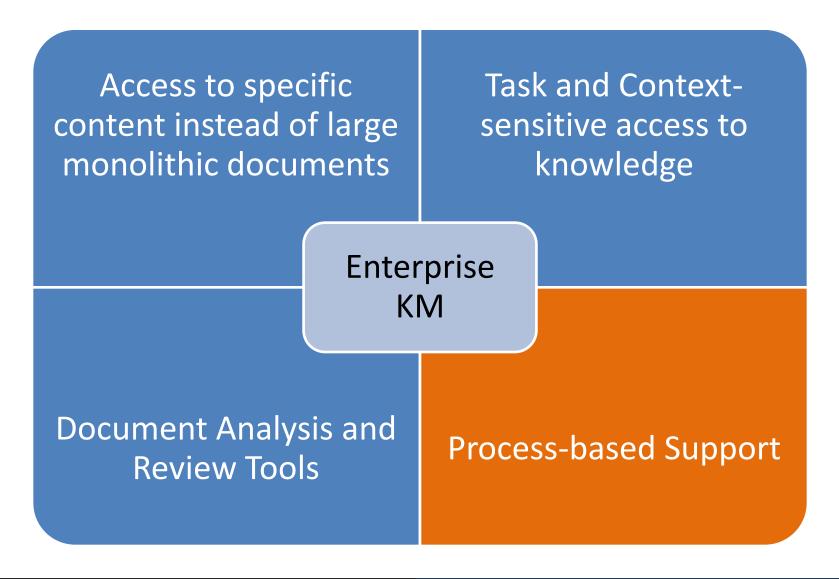
Areas of Improvement

Task and Context-Access to specific content instead of large sensitive access to monolithic documents knowledge Enterprise KM **Document Analysis and** Process-based Support **Review Tools**





Areas of Improvement



Publishing Enterprise Content Today

Gather

- KM team gathers project materials
- Filters out "irrelevant" stuff

Upload

- They bundle up docs & tag them
- Bundles are uploaded

Tag

 Create indices and tag with enterprise taxonomies to organize bundles

Encouraging Content Submission

- Constantly monitor laptop hard drives and index new documents
- Classification system to tag new documents

Some Metadata fields

Industry

• Automotive, Financial, Electronics, Government, Retail, Forestry, Products,...

Offerings (OGs)

 Products, Strategy, CRM, Supply Chain, Resources,...

Doc type

• Offering, Proposal, Credential,...

Business Function

 Accounting, Learning, HR, Outsourcing, Program Management,...

Level 2 subcategories branch out x10

Ordering Sequential Prediction Tasks

Determine order of tasks to maximize overall performance

Intractable

- Approximation (Lad et al. SDM 2009):
 - Find Pairwise Preferences
 - Combine to form an optimal ordering

Distributed Active Learning

- Querying the user offers many interesting problems for active learning
 - Online only? No pool of instances available.
 - Query for all contributions by a user Structured example?
 - Constraints/Dependencies among labels for contributions

Querying KM team members might even have structure

Confidentiality Issues

- Structured Data Guessing Anonymity (Rachlin et al.PinKDD 2008)
- Challenge: Unlike structured data, text does not contain identified sensitive attributes

- Tension: Redact documents while still preserving some aspect of the utility (Cumby, ECML 2009 Demo)
- K-confusability

Summary

Access to specific content instead of large monolithic documents

Task and Contextsensitive access to knowledge

Enterprise KM

Document Analysis and Review Tools

Process-based Support

Enterprise KM: A different perspective

The Consumer's Life



The Consumer's Life









Crowd:

Te Knowledge:

Na Pervasive Bo Rich Co Accessible



Loose Organization
Scalable Efforts
Transparency

Work Life



Work Life







Knowledge: Te

Sparse A⁽ Siloed Stale

Crowd:

A burden, rather than an opportunity.

Rayid (

ture Technology Labs

Personalized Knowledge Models



Vs.



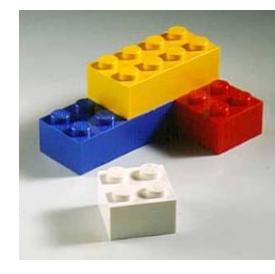
MyKM

In the enterprise: Top Down: "This is what you will use"

In the outside world: Bottom Up: "I choose or make what I'll use"

enterprise information.

"Lego blocks" that will let our community make the tools they can use to provide and consume



Clothing Retailer



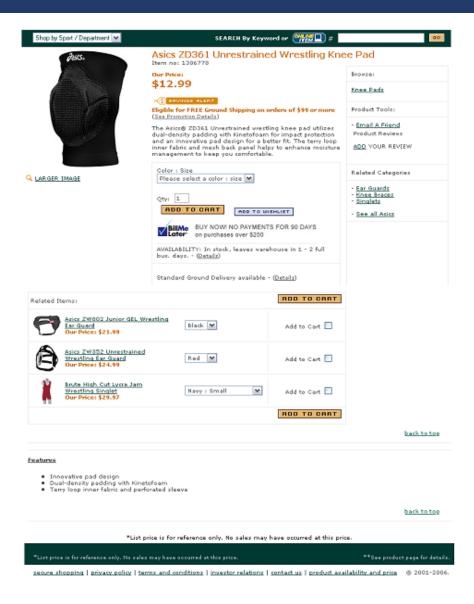


Lauren by Ralph Lauren Catlin Twill Pant \$89.50

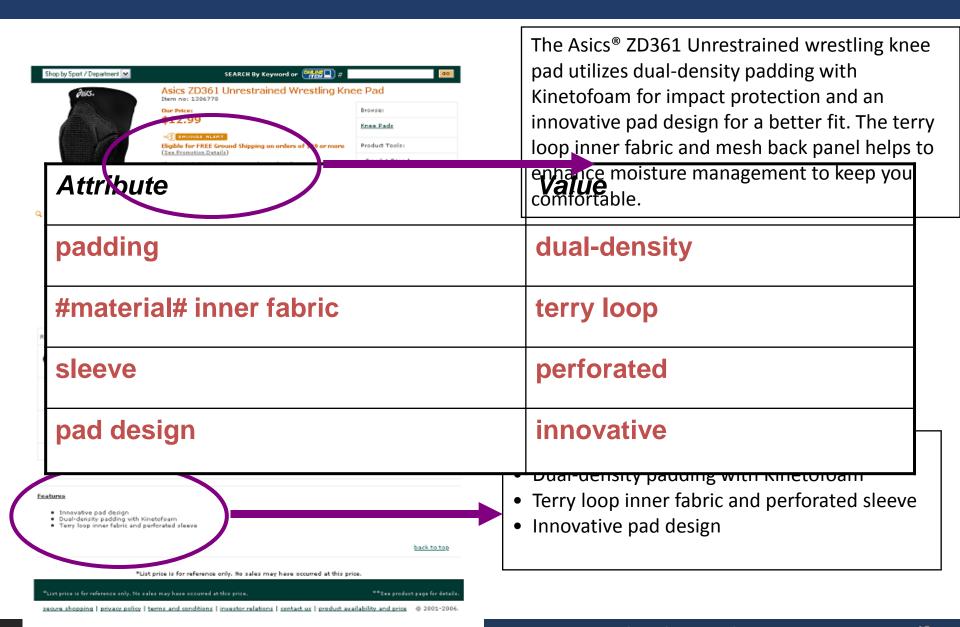
A sophisticated pant in substantial cotton twill is contoured for a sleek silhouette.



Sporting Goods



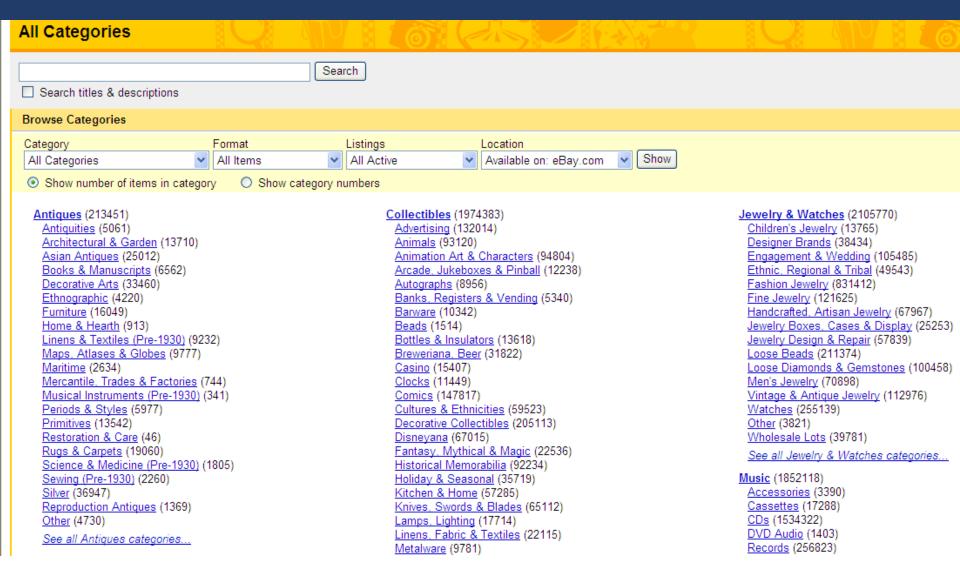
Sporting Goods



Challenge: How do you describe these products?



Extreme Case: eBay



Having a product attribute database allows....

 Transfer learning from campaigns to related products and categories and scale to a large number of products efficiently

 Dealing with the Cold-start problem especially for fast-changing categories

Ad networks and aggregators to learn across client











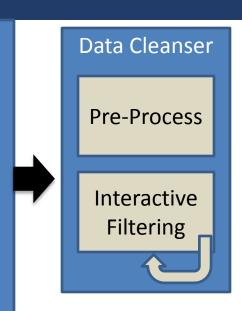


What can businesses do with such enriched databases?

- Assortment optimization
 - Sample Questions: Do people buy Bic Gel Grip Pen because of the brand being Bic or the Gel grip?
- Supply chain management
 - Sample Question: Are these two products comparable?
- Procurement
 - Sample Question: What should I buy and from whom?
- Marketing
 - Sample Question: How should I talk about my products?
- Competitive Intelligence:
 - Sample Question: How many high-end TVs does my competitor sell as compared to me?
- Product lifecycle planning
 - Sample Question: How do products change over time?

Challenges

- Signal/noise ratio
 - Extra information
- Labeled data is noisy/misleading
- Heterogeneous sources (title, desc, tables)
- Adhoc sellers
- Typos
- Looooong sentences



Data

Pre-Processing





Remove Extraneous Sections



Remove Extraneous words (and text following them)



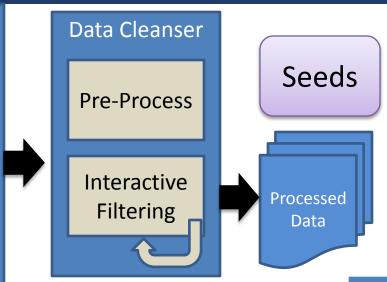
Remove Low-Frequency Words (2<n<10)



Interactive Description
Processing using
unsupervised
clustering (10<k<50)



| Keep | Cluster ID | Descriptive Words | Size |
|------|------------|--|-------|
| | 1 | guarantee, free, worldwide, ship, anywhere | 35432 |
| X | 2 | Chevy, grand, front, wheel, silver | 21211 |
| X | 3 | Tire, rubber, tread, michelin, goodyear | 5000 |
| X | 4 | #number#, model, make, year, all | 4323 |
| | 5 | Return, carefully, package, accepted | 3244 |



Data

| Attributes | Values | Neither |
|------------|----------|---------|
| Make | 2000 | And |
| Model | Fiat | Is |
| Year | Bmw | Over |
| Condition | Goodyear | |
| | | |
| | | |
| | | |

Unsupervised Seed Augmentation

- Goal: High Precision and Low Recall
- Intuition: Attributes and Values often occur as pairs of consecutive words where the 1st word is the value and 2nd is the attribute
 - Back pocket, side pocket, front pocket
- 2nd word shouldn't occur with the same word every time (phrase) and also shouldn't occur with "too many" words
 - Pittsburgh Steelers, Fifth Avenue, running across

Unsupervised Seed Generation

- All bigrams $w_j w$ are considered candidates for attribute-value pairs:
 - $-w_i$ is a potential value and w is a potential attribute
- Let w_j (with 0<j<k) be the set of unique words that occur just before w
- Sort all w_j from highest to lowest $P(w_j | w)$
- Retain all w_j such that the sum of the highest-ranking $p(w_j/w) = z$ (we use z=0.5)

Compute cumulative mutual information:

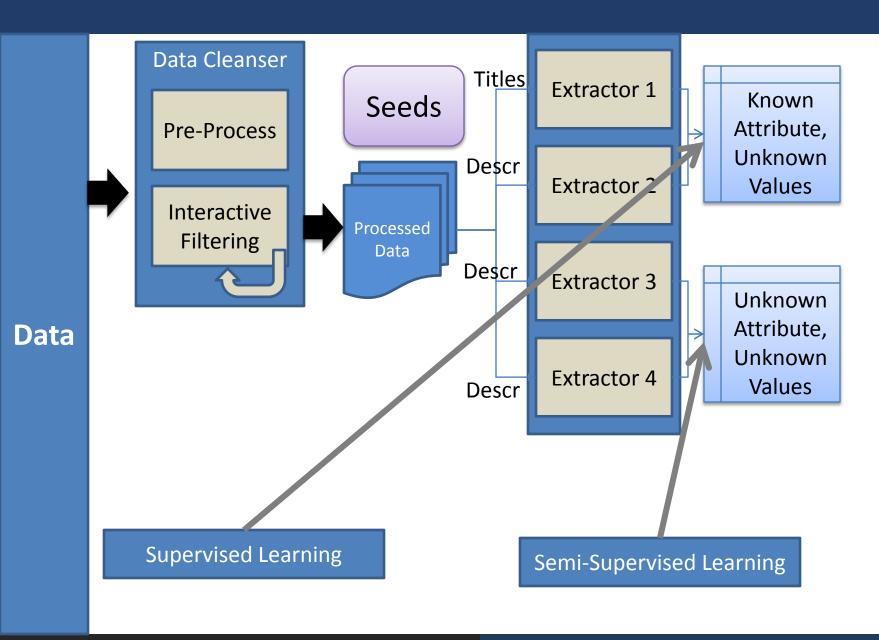
- Let
$$p(w,w_{1...k}) = \sum_{j=1}^k p(w,w_j) \text{ . Then,}$$

$$cmi(w_{1...k};w) = \log \frac{p(w,w_{1...k})}{(\lambda * \sum_{j=1}^k p(w_j)) * ((\lambda - 1) * p(w))}$$
 where $0 < \lambda < 1$.

Retain as pairs those whose c.m.i. exceeds a threshold.

Examples of extracted attribute-value pairs

| Attribute | Values |
|-------------|----------------------------|
| case | carrying, storage |
| | |
| compartment | main, racquet |
| pocket | ball, welt, side-seam, key |
| | |



Titles

Supervised Learning

Sequential Classification

Descriptions

Supervised Learning from Title: Apply to Description

Supervised Learning from Title: Apply to Description

 Semi-Supervised Learning from Title: Apply to Description

Learning Patterns from Tables

Classification: Co-EM with Naïve

- Split data into two views:
 - View1: stemmed word itself and POS tag
 - View2: 8-word context and their POS tags

- Training data for first classification iteration:
 - Seeds extracted in previous step
 - Lists of generic attributes: countries, colors, materials

Classification: Co-EM with Naïve Bayes

- General Co-EM procedure:
 - 1. Initialize based on labeled data
 - 2. Train view1 classifier, label view1 of unlabeled data
 - 3. Use view1 labels to train view2 classifier
 - 4. Label view2 of unlabeled data using view2 classifier
 - 5. Repeat 2, 3, and 4
 - 6. Use both classifiers to get final probabilities on unlabeled data

Classification: Co-EM with Naïve Bayes

 When labeling view2, estimate word and class probabilities using:

- Current assignments of classes to view1 words (use probability distribution over all classes)
- Co-occurrence counts of view1 words with each view2 word (how often did a view1 word appear in view1's context)
- Reverse procedure when labeling view1

Training View2 from View1

• Estimate new view2 class prior probabilities:

$$P(c_k) = \frac{1 + \sum_{i=1}^{n_1} cnt(view1_i) * P(c_k|view1_i)}{numclasses + \sum_{i=1}^{n_1} cnt(view1_i)}$$

Estimate new view2 word probabilities:

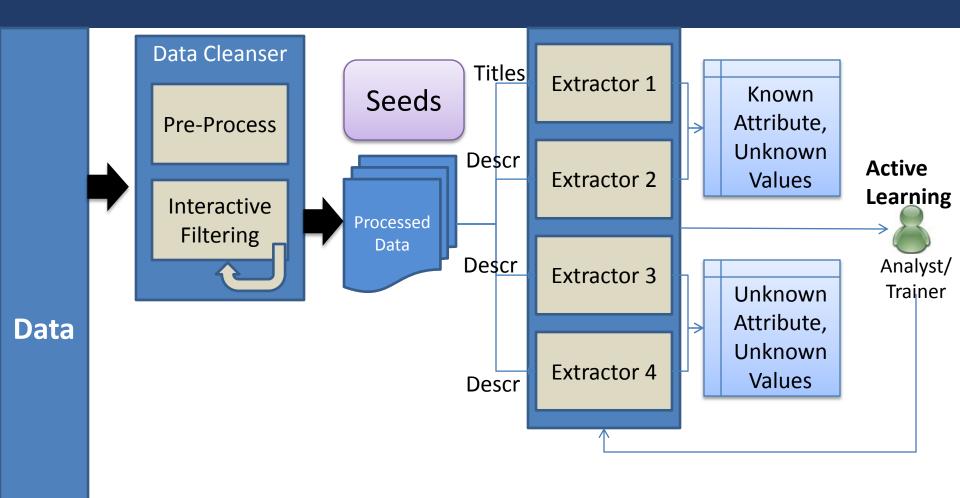
$$P(view2_j|c_k) = \frac{1 + \sum_{i=1}^{n_1} cooc(view1_i, view2_j) * P(c_k|view1_i)}{n_2 + \sum_{i=1}^{n_1} cooc(view1_i, view2_j)}$$

Label view2 words:

$$P(c_k|view2_i) \propto P(c_k) * P(view2_i|c_k)$$

Use both view1 and view2 classifiers to label unlabeled data

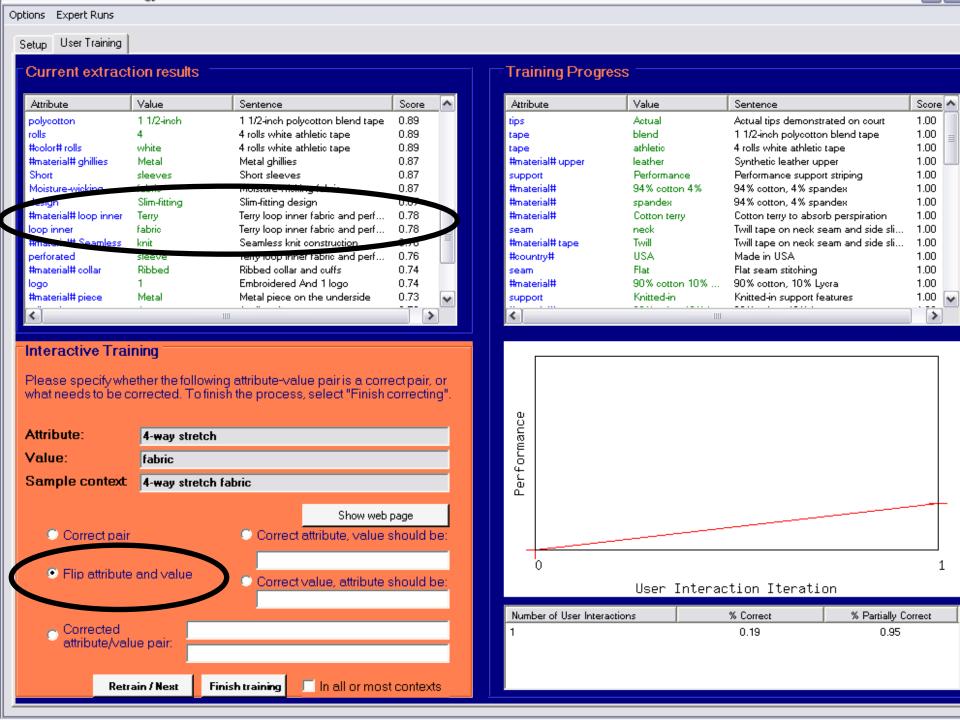
$$P(c_k | < view1_i, view2_j >) = \frac{P(c_k | view1_i) + P(c_k | view2_j)}{2}$$

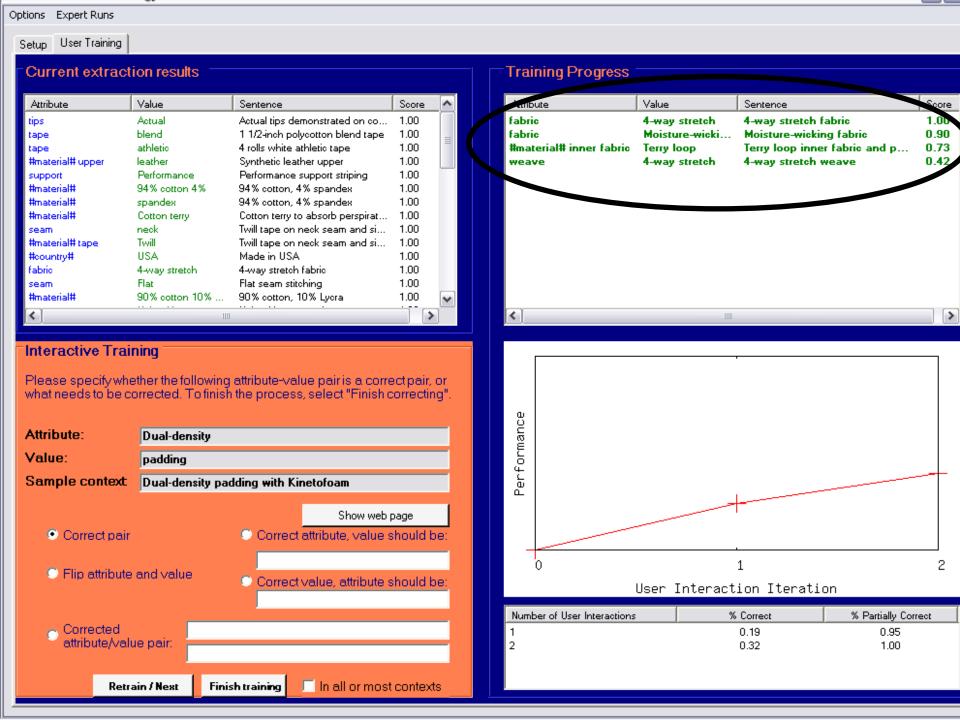


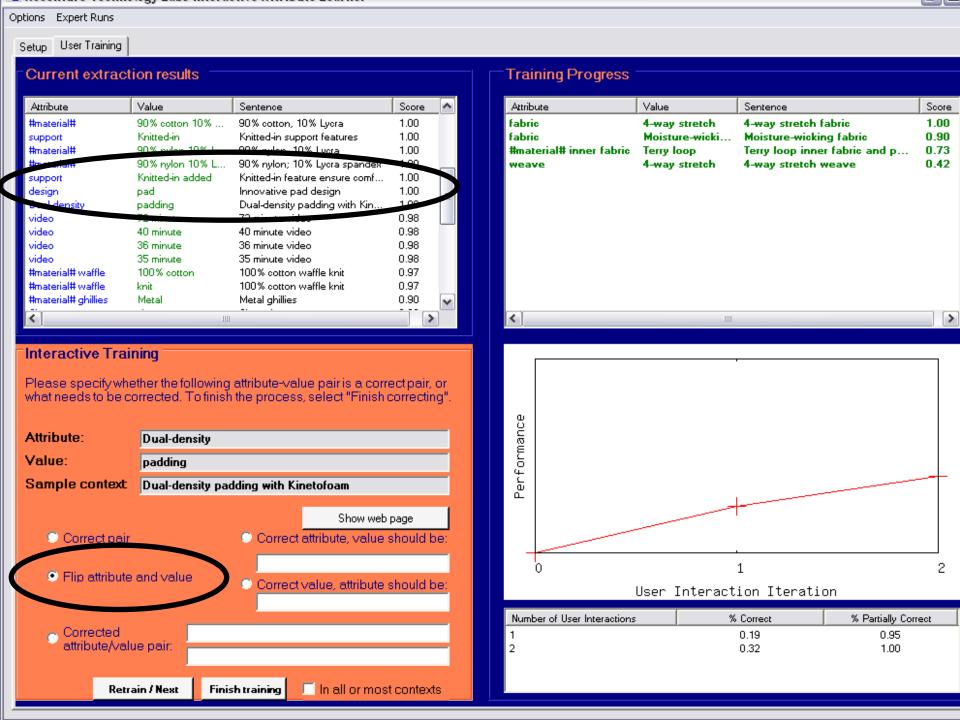
Active Learning

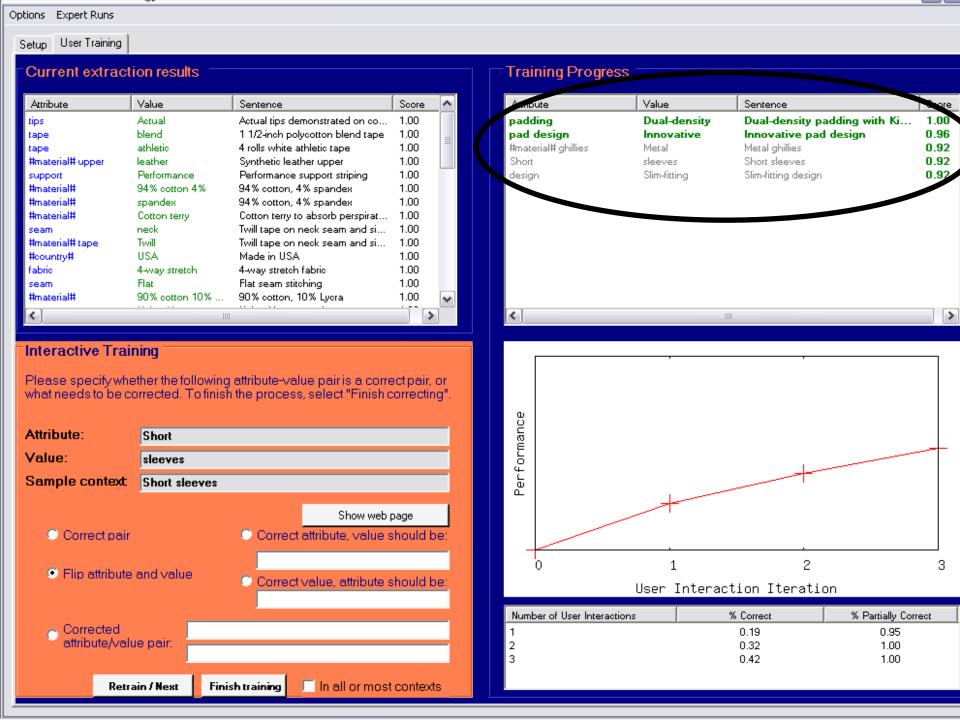
Muli-view Semi-supervised + Active Learning

- Variety of metrics
 - Frequency
 - -KL
 - Frequency weighted KL
- Interactive version of co-EM + NB
 - Orders of magnitude faster (from 15 minutes to 10 seconds)









Experimental Results

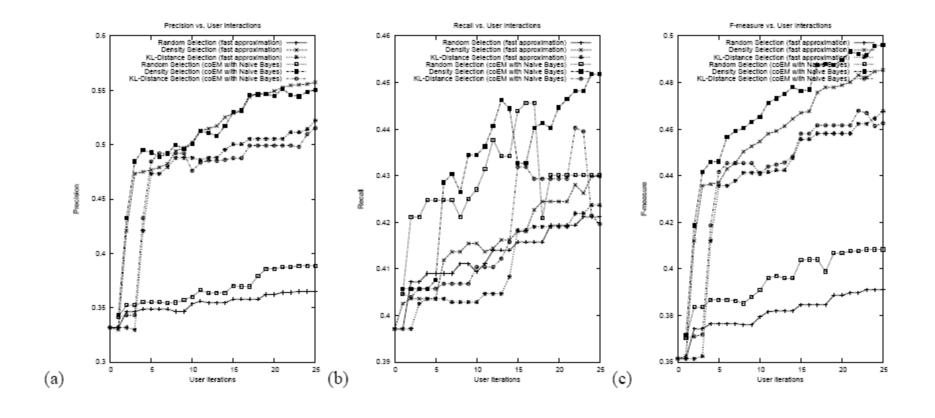


Fig. 1. Precision, Recall, and F-measure for fast algorithm compared to coEM with naive Bayes. The y-value for k indicates the recall, precision, and F-measure after the kth user interaction.

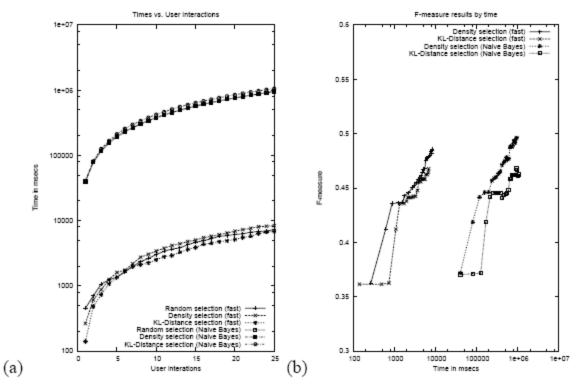
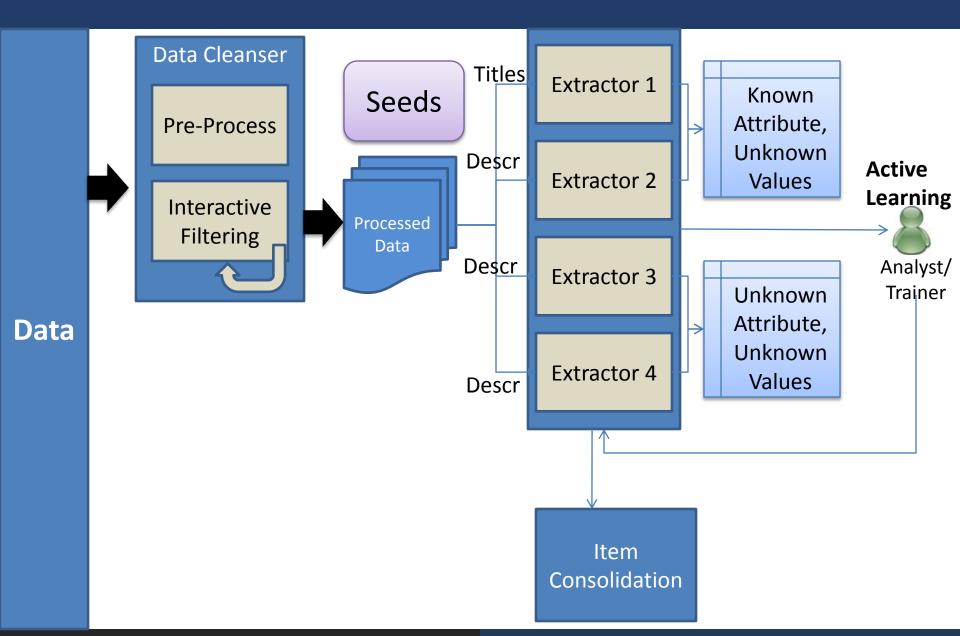


Fig. 2. Time comparison between Fast algorithm and coEM with naive Bayes. In (a), the y-value for k indicates the time the user needed to wait until the k^{th} user interaction.



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Forming attribute-value pairs

- Classification results in single words labeled as attributes, values, or neither, but many attributes are phrases
 - Merge adjacent words with the same label and with high correlation scores (chi^2, yule's Q, m.i.)
- Link attribute phrases and value phrases to form pairs
 - Syntactic dependencies (Minipar)
 - As fallback, also link phrases that have high correlation score or are adjacent
 - Add known attributes that are implicit but present in our KB
 - Assess whether unlinked attributes are "binary"

Examples

| l Example | Attribute | Value |
|---|----------------------------------|----------------------|
| 1 1/2-inch polycotton blend tape | polycotton blend tape | 1 1/2-inch |
| 1 roll underwrap | underwrap | 1 roll |
| 1 tape cutter | tape cutter | 1 |
| Extended Torsion bar | bar | Torsion |
| Synthetic leather upper | #material# upper | leather |
| Metal ghillies | #material# ghillies | Metal |
| adiWear tough rubber outsole | rubber outsole | adiWear tough |
| Imported | Imported | #true# |
| Dual-density padding with Kinetofoam | padding | Dual-density |
| Contains 2 BIOflex concentric circle magnet | BIOflex concentric circle magnet | 2 |
| 93% nylon, 7% spandex | #material# | 93% nylon 7% spandex |
| 10-second start-up time delay | start-up time delay | 10-second |

Examples of extracted pairs for system run with co-EM

Interesting Results

- New Domain Attributes
 - Cyl (Cylinders)
 - Logo
 - Hub Bore
 - Lip
 - Warranty
 - Included
 - Donor Vehicle
 - Shown

Interesting Results

- New values discovered for Tire Type:
 - Suv
 - Minivan
 - Snow
 - trailer
 - Offroad
 - boat.

Context-dependent extraction

- Misleading terms
 - 'Other:', skype:'
- Typos:
 - 'finnish' as an attribute
- POS-dependent
 - 'Bolt' (NP) = attribute (Bolt Pattern)
 - 'Bolt' (VP) = neither (bolts on to)
- 'Style'
 - 4 new 17x8 Morxchn Mustang Cobra R style deep lip wheels
 - We only guarantee it to fit the same Make Model Year and Body Style as its donor vehicle

KL metric is useful in detecting confusable words

- interga
- quntity

Summary

 Businesses are not very good at capturing all the structure in their data

 Machine learning can help make that process faster, "better", and cheaper

 The same techniques are applicable in the semantic web to help create, maintain, and update ontologies

Summary

 Traditional Enterprise Knowledge Management has interesting research challenges

 Next generation KM systems are likely to be personalized mash-ups with personalized knowledge models

Opportunity for semi-automated semantic learning approaches