### **Latent Semantic Mapping**

**Exposing the Meaning behind Words and Documents** 

Session 136

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Senior Software Engineer

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### **Session Overview**

- What is LSM?
- How does it work?
- Using LSM
- Case studies
- Your application here
- Q&A

### What Is Latent Semantic Mapping?

A technology to analyze text documents according to their meaning and classify them by topic

...allow me to demonstrate

# Demo A simple LSM example

### Some LSM Applications

- Junk mail filter
  - Assess whether mail message is legitimate or spam
- Parental controls
  - Assess whether web page contains explicit words or other objectionable material
- Kana to Kanji conversion
  - Use topic of a document to disambiguate between ambiguous characters
- Localization
  - Use underlying topic of discourse to aid in string translation

### How Does It Work?

Jerome Bellegarda, Ph.D.

Apple Distinguished Scientist

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### It Is All in the Name!

- "Mapping"
  - Represent words and documents as points in multidimensional space
  - From discrete to continuous entities
- "Semantic"
  - Mapping aimed at uncovering global fabric of language
  - Based on overall content/meaning of documents
- "Latent"
  - Meaning not obtained from a dictionary, but inferred directly from data
  - Based on word co-occurrences, automatically handle synonyms and multiple senses

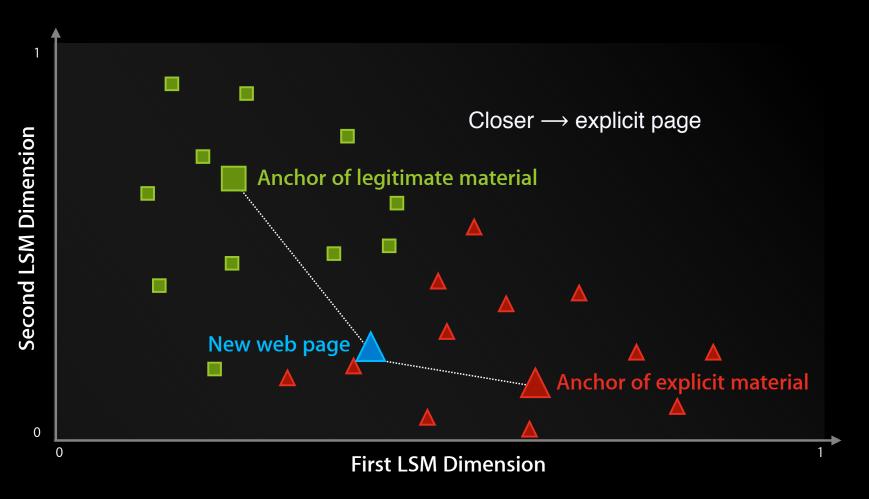
### Latent

- Word co-occurrences
  - Words A and B present in the same document
  - Words A and C present in doc 1, words B and C present in doc 2
  - Words A and B "close" in LSM space
- Discover synonyms
  - "car" vs. "automobile"
  - "bank" vs. "financial institution"
- Discover multiple senses
  - "bank" + "rate" (→ finance)
  - "bank" + "river" (→ fishing)

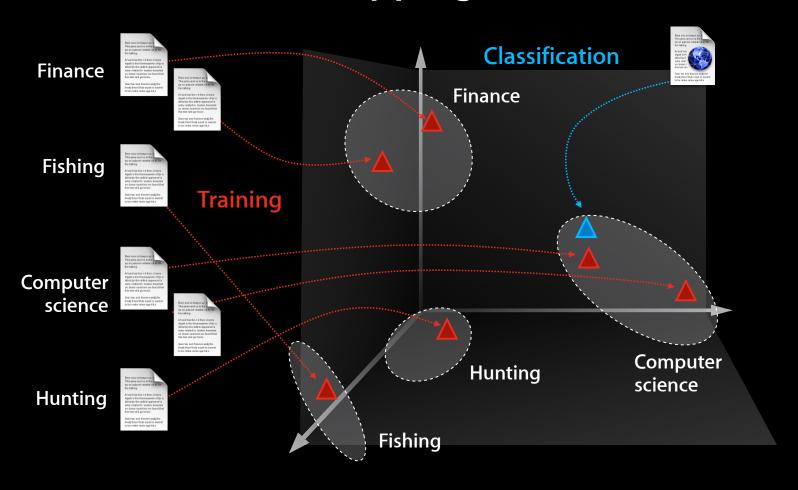
### Semantic

- Example: parental controls
  - Assess whether web page is free of objectionable material
  - Separate "sex toys" from "sex education" (using underlying meaning)
  - Can leverage closeness in LSM space
    - "sex" + "toys" (→ probably objectionable)
    - "sex" + "education" (→ probably ok)
- LSM Implementation
  - Use two categories (one for explicit material, one for legitimate material)
  - Define two semantic anchors in LSM space
  - Evaluate each incoming web page against these two anchors



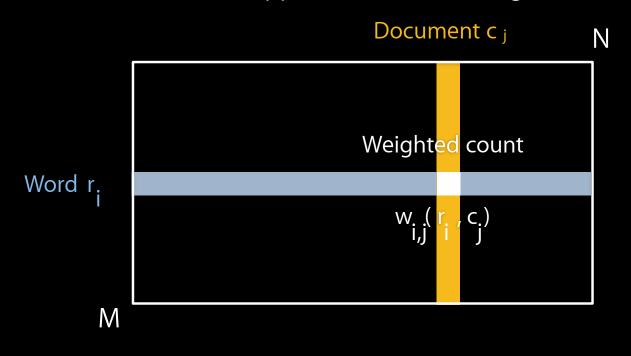


### Mapping



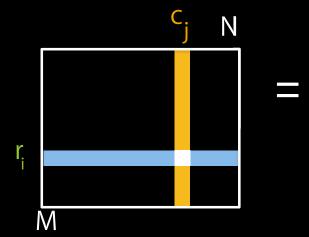
# It Is Not (All) Magic! Basic info

- How often does each word appear in each document?
- How often does each word appear in entire training data?

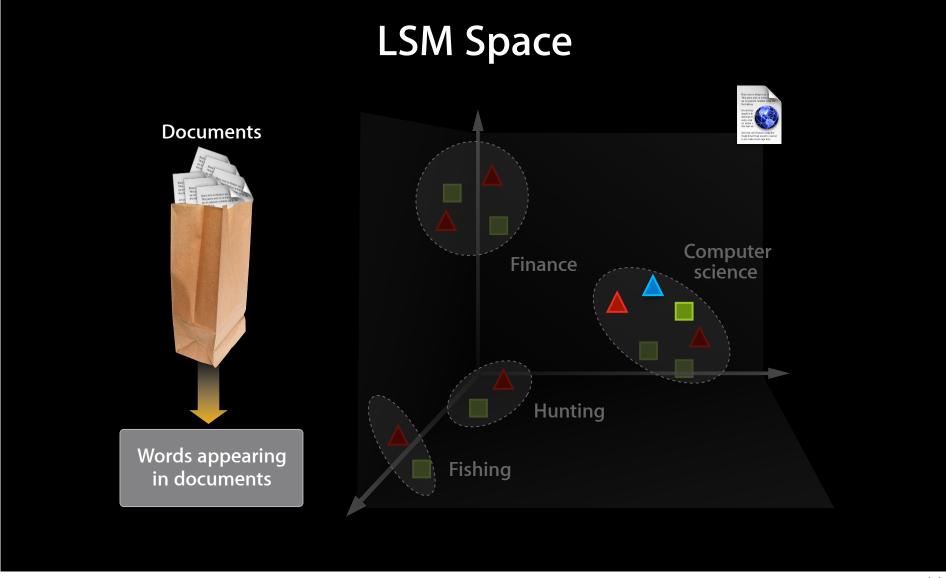


### Singular Value Decomposition (SVD)

$$W_{(M\times N)} =$$



R: Number of dimensions retained



### **Caveats**

- Intrinsic descriptive power
  - Shallow sense of "semantic" (tied to co-occurrences)
    - No actual "natural language understanding"
  - Word order is ignored ("bag of words" modeling)
    - Local constraints need to be added explicitly
- Critical importance of training data
  - Ambiguity: "river bank" and "Bank of Cupertino" in same doc?
  - Writing style: Wall Street Journal vs. Associated Press
- Offline training cost (in some apps)
  - SVD can take a long time with large matrices

### Clustering

- Problem of ill-defined categories
  - In Kana to Kanji conversion, topic information is used to disambiguate between ambiguous characters
  - Analogous to "the tale of a princess" vs. "the tail of a peacock"
  - But Japanese corpus contains over 300,000 documents
  - How to best extract and leverage topic information?

### Clustering (Cont.)

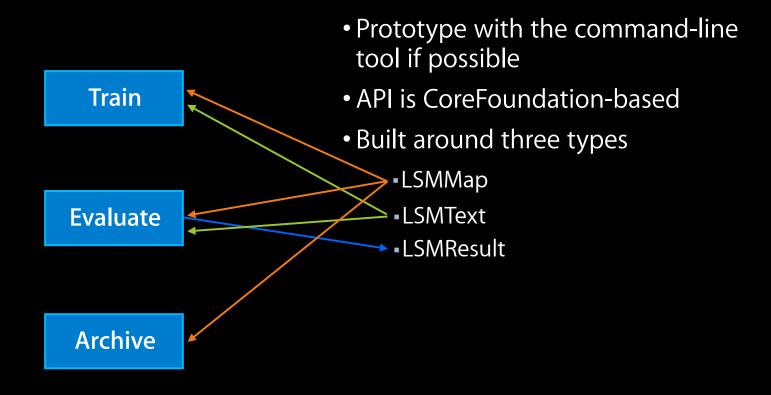
- Two solutions
  - Manual assignment of documents into topics (categories)
  - LSM clustering
    - Initial LSM space where each document is a separate category
    - Data-driven clustering to reduce number of categories
    - (Optionally) new LSM space using clustered data

### Two Implementations

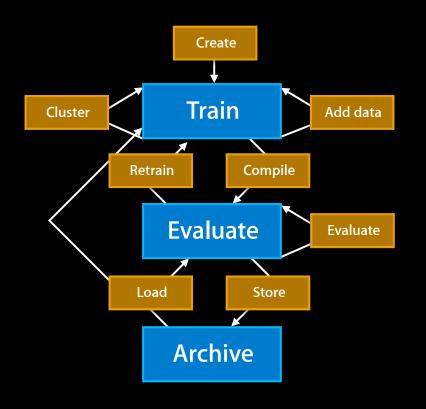
- K-means clustering
  - Pick initial cluster centroids ("seeds")
  - Compute distances to these centroids
  - Adjust centroids accordingly and iterate
  - Caveat: sensitive to initial cluster assignment
- Agglomerative clustering
  - Compute all pair-wise distances between points
  - Merge closest pair, replace by its centroid
  - Adjust affected distances and iterate
  - Caveat: prohibitive for large data sets

## Using the LSM API

### Basics of LSM Programming



### **Using LSM Maps**



LSMMapCreate

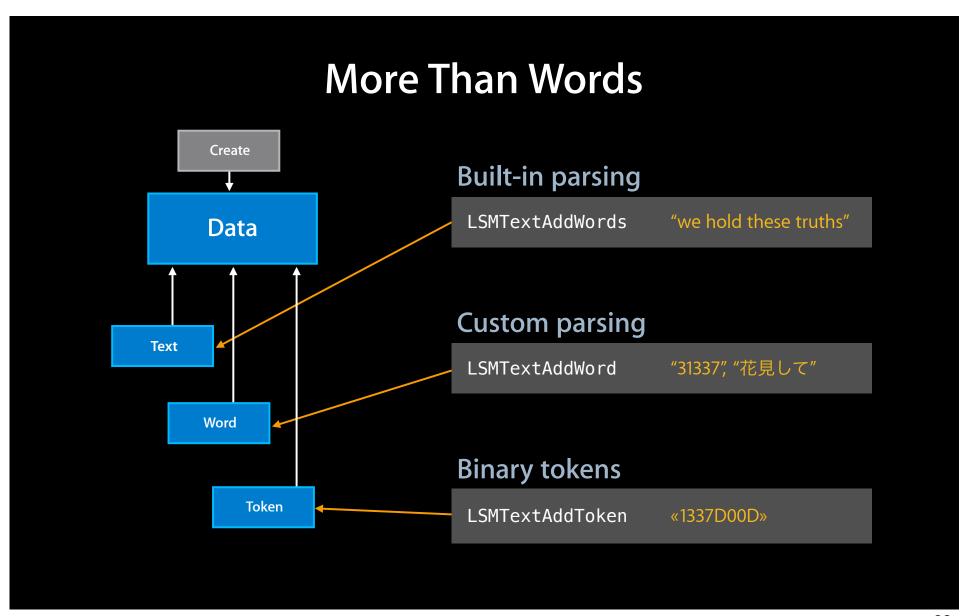
LSMMapAddCategory LSMMapAddText

LSMMapCompile LSMMapStartTraining

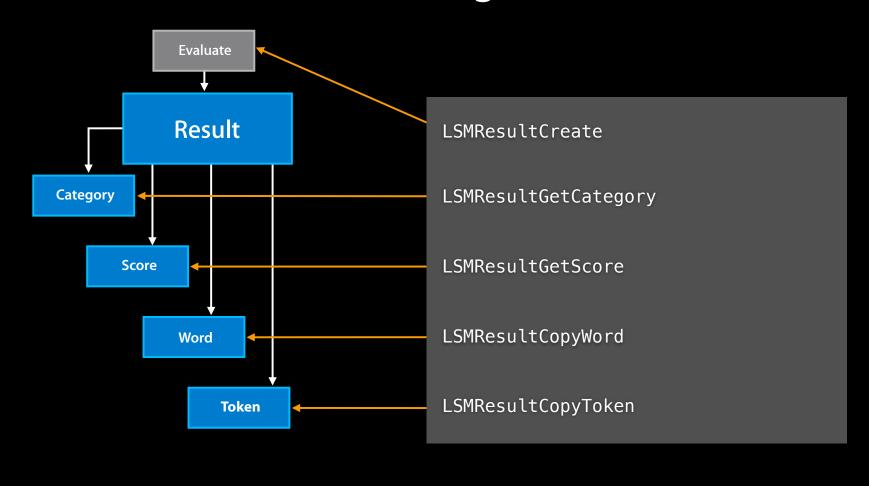
LSMResultCreate

LSMMapWriteToURL LSMMapCreateFromURL

LSMMapCreateClusters LSMMapApplyClusters



### **Evaluating a Text**



# **Case Studies**

### Case Study: Junk Mail Filtering

- Two categories: legitimate/junk
- Biased toward legitimate

```
LSMResultGetCategory(res, 0) == kJunk
&& LSMResultGetScore(res, 0) > kJunkThreshold
```

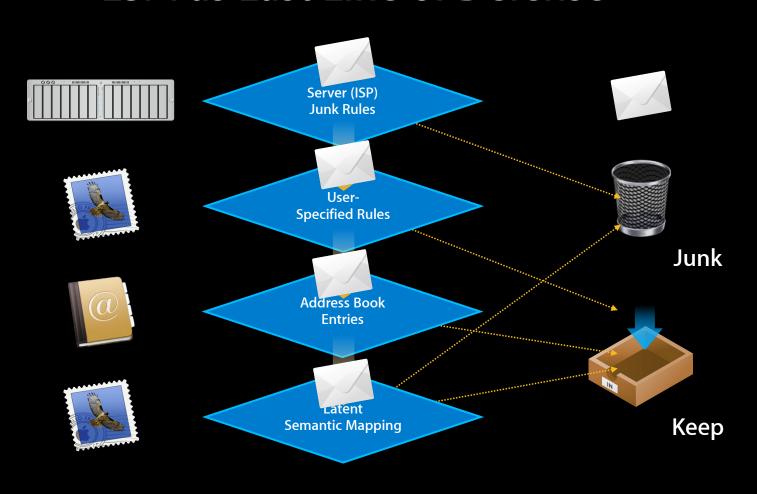
• Parsing can be difficult: m.o.n.e.y, víåg®ä

```
LSMTextAddWords(text, words, NULL, kLSMTextApplySpamHeuristics);
```

Map contains all sorts of offensive words

```
LSMMapCreate(kCFAllocatorDefault, kLSMMapHashText);
```

### LSM as Last Line of Defense



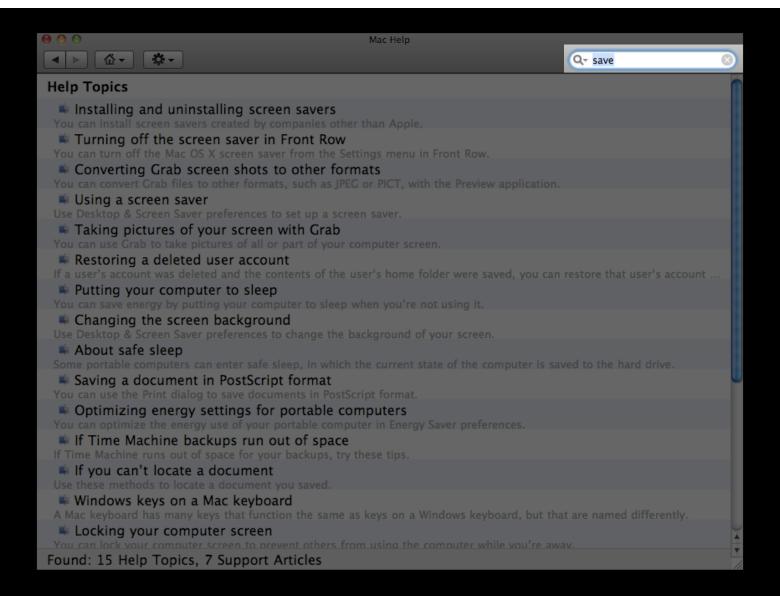
### Case Study: Help

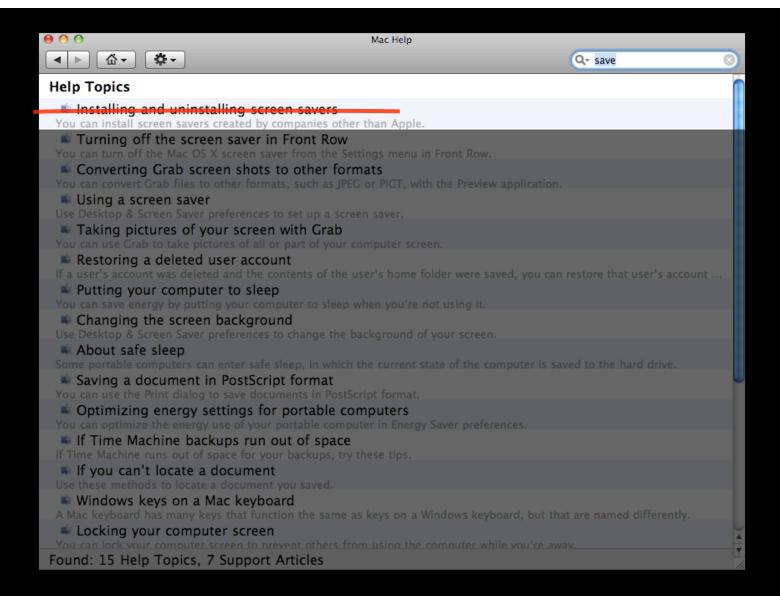
Kim Silverman, Ph.D. Principal Research Scientist

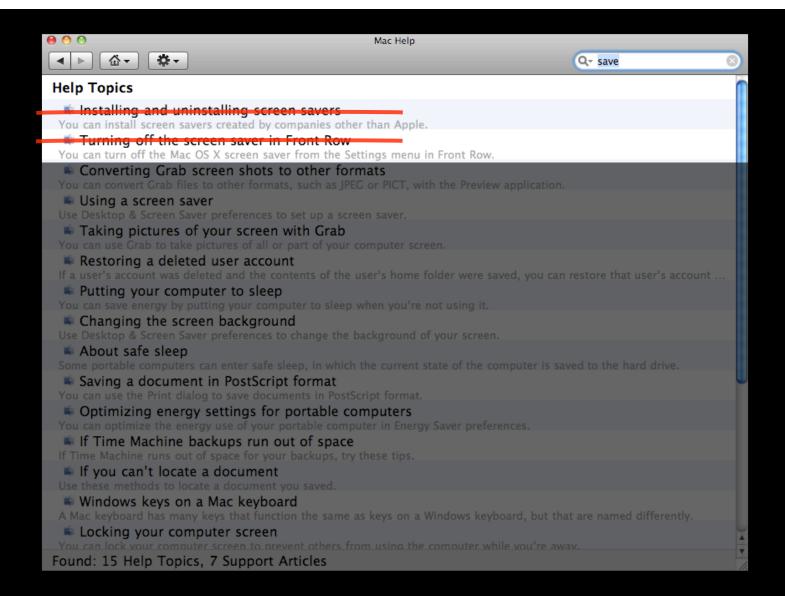
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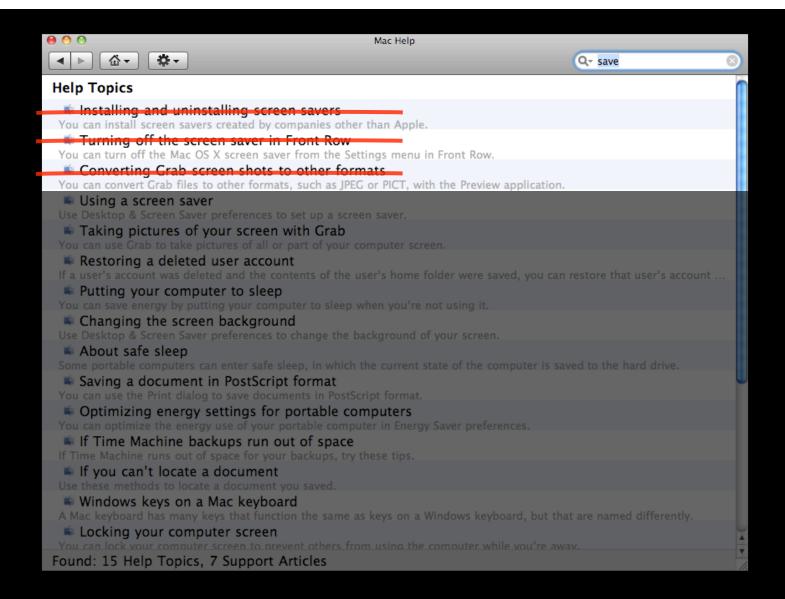
### Problem

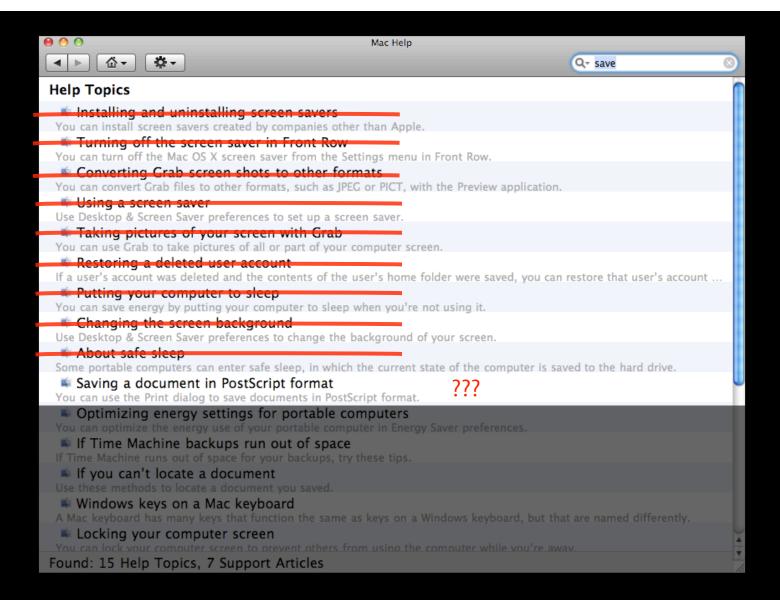
• Unsatisfying results when people type queries to help







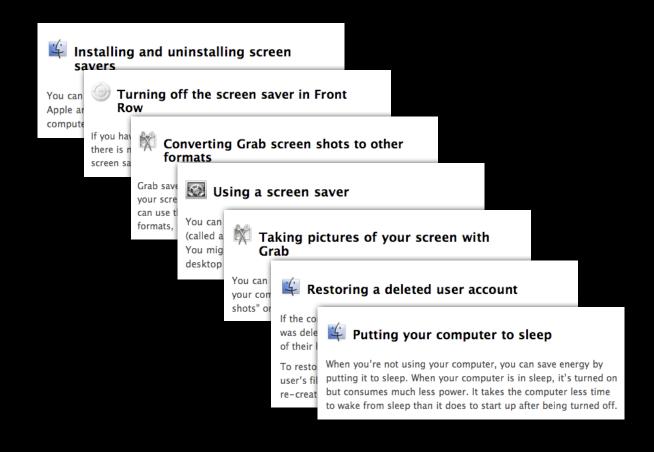




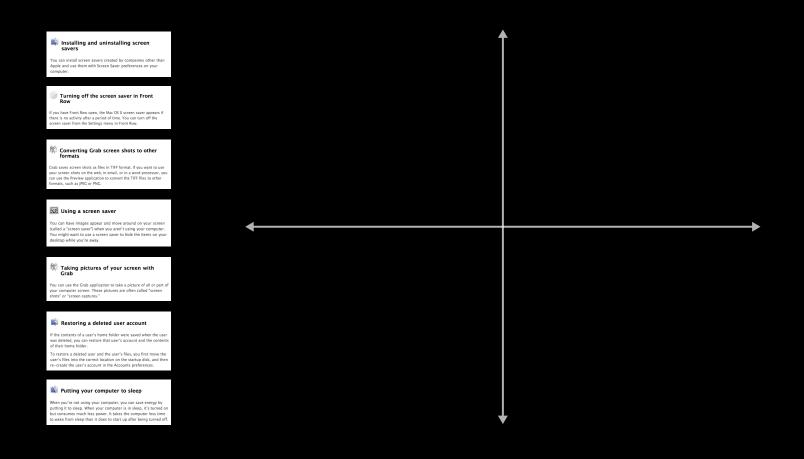
### **Current Approach**

- Look for documents that contain words in the query
- Use hand-inserted synonyms for common typos, different forms of words, etc.

### **Latent Semantic Mapping**



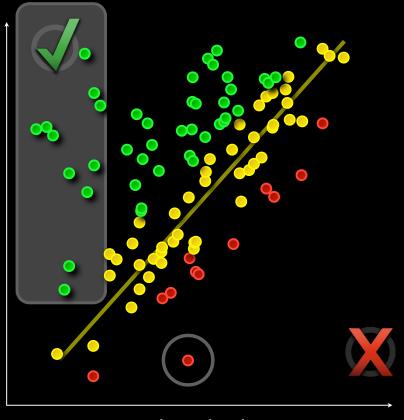
### **Latent Semantic Mapping**



# **Latent Semantic Mapping**



# **100 Queries**



LSM Search Relevance

- LSM better
- About the same Keyword better

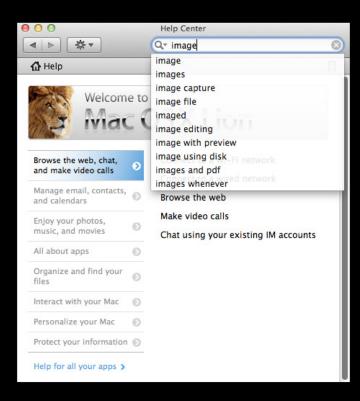
**Keyword Search Relevance** 

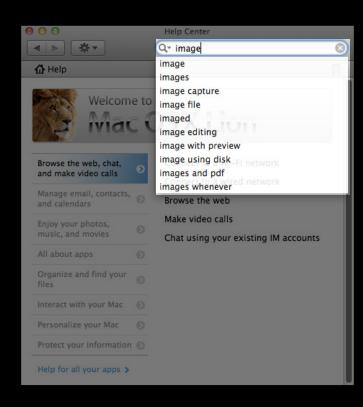
# How to Improve LSM Results

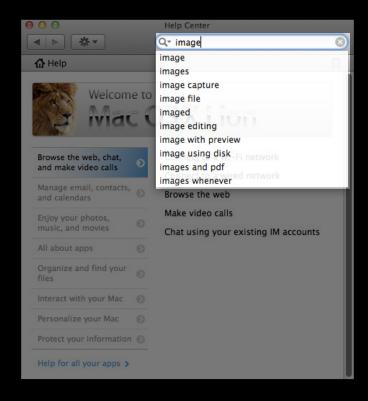
# Preprocessor Preprocessor Results

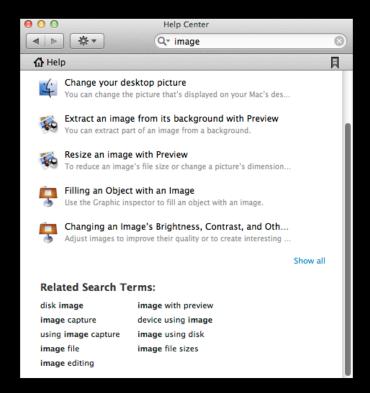
# **Preprocessing Text**

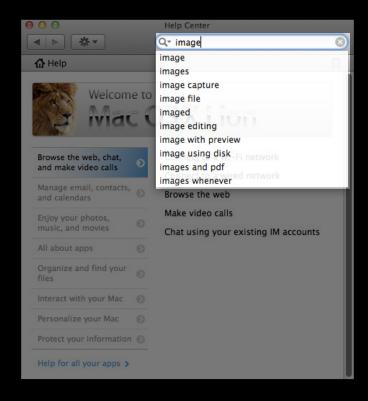
- Use n-grams
  - Word pairs, word triplets
    - e.g., "double click" vs. "key click"
- Remove unwanted/irrelevant text
  - HTML tags
  - "click here", "return to contents"
- Stemming
  - "save" -> saves, saved, saving
  - But not "saver"

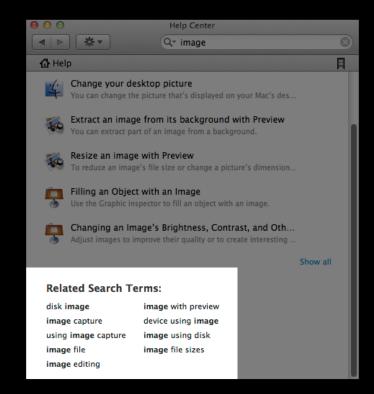












Filter nearest n-grams

Clean up your workspace

Set up your workspace

Filter nearest n-grams

Clean up your workspace

Set up your workspace



# Making LSM Work for You

# What Can LSM Categorize for Me?

- Bookmarks
- RSS feeds
- Books/CDs/DVDs (by fetching reviews/abstracts)
- Wines and cheeses
- DNA sequences

•

#### **Guidelines**—**General**

- Can LSM handle the task?
  - Problem is syntactic in nature
    - "Find dates, times, email addresses, etc."



"Sort documents by topic"



- Are the categories distinct enough?
  - Economy vs. business
  - Economy vs. entertainment



# Guidelines—Testing

- Validation data
  - Partition training data into 10 random chunks
  - Train on first nine chunks, test on last (held out)
  - Repeat sequentially (round-robin) and average results

# Guidelines—Testing (Cont.)

- What if outcome looks strange?
  - Try again with (short) stopword list
    - Words appearing roughly equally in all categories ("the", "in")
  - Try experimenting with number of dimensions
    - Default is number of categories, but for natural language problems use between 100 and 300

# **Guidelines**—Training

- Quality of training data
  - Representative of full breadth of domain
  - As balanced as possible in each category

# **Guidelines**—Training (Cont.)

- Quantity of training data
  - Large enough to cover variability
  - Rule of thumb for large vocabulary applications
    - Preferably > 30,000 unique words
  - Larger as more categories are added
  - Larger still if data changes over time (for example, news)

#### **Final Recommendation**

#### Integrate LSM with other source(s) of knowledge

- LSM tends to complement other techniques
  - It often can improve the robustness of the overall system
- Example 1: Junk Mail filter
  - Complements (instead of replacing) white lists, black lists, and handwritten rules
- Example 2: Kana to Kanji
  - Conversion uses LSM as an additional source of information to be exploited in final decision

# Go Forth and Map Some Text!

For More Information...

#### **More Information**

#### **Bill Dudney**

Application Frameworks Evangelist dudney@apple.com

#### **Mailing List**

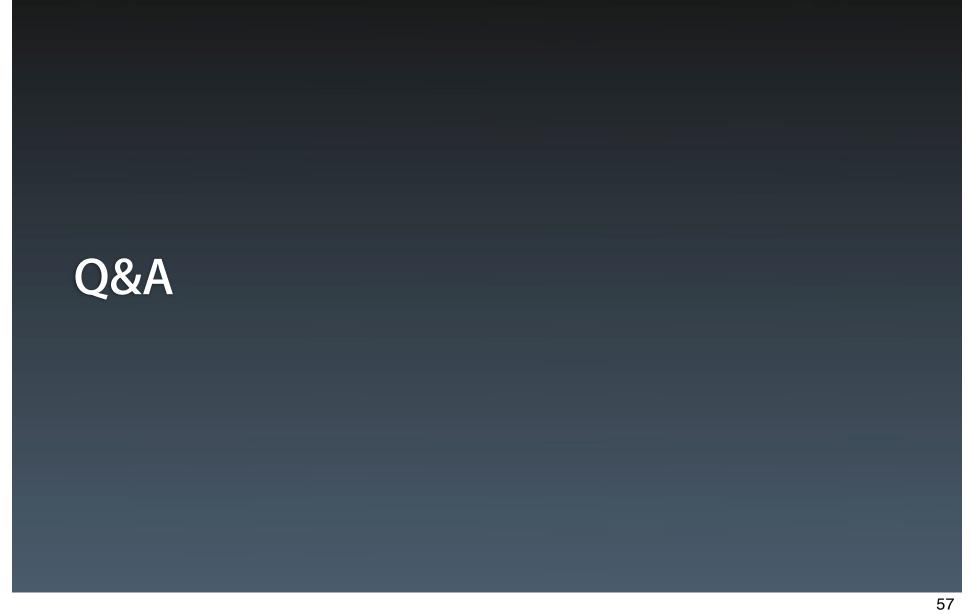
Latent Semantic Mapping Mailing List http://lists.apple.com/mailman/listinfo/latentsemanticmapping

#### **Documentation**

Latent Semantic Mapping Reference http://developer.apple.com/documentation/TextFonts/Reference/LatentSemanticMapping/index.html

#### **Apple Developer Forums**

http://devforums.apple.com



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