# CS276B
Text Information Retrieval, Mining, and Exploitation

Lecture 12
Text Mining I
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(includes slides borrowed from Marti Hearst, )

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# The Reason for Text Mining...

**Amount of information**



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# Corporate Knowledge "Ore"

- Email
- Insurance claims
- News articles
- Web pages
- Patent portfolios
- IRC
- Scientific articles
- Customer complaint letters
- Contracts
- Transcripts of phone calls with customers
- Technical documents

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# Text Knowledge Extraction Tasks

- Small Stuff. Useful nuggets of information that a user wants:
    - Question Answering
    - Information Extraction (DB filling)
    - Thesaurus Generation
- Big Stuff. Overviews:
    - Summary Extraction (documents or collections)
    - Categorization (documents)
    - Clustering (collections)
- Text Data Mining: Interesting unknown correlations that one can discover

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# Text Mining

- The foundation of most commercial "text mining" products is all the stuff we have already covered:
    - Information Retrieval engine
    - Web spider/search
    - Text classification
    - Text clustering
    - Named entity recognition
    - Information extraction (only sometimes)

- Is this text mining? What else is needed?

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# One tool: Question Answering

- Goal: Use Encyclopedia/other source to answer "Trivial Pursuit-style" factoid questions
- Example: "What famed English site is found on Salisbury Plain?"
- Method:
    - Heuristics about question type: who, when, where
    - Match up noun phrases within and across documents (much use of named entities
        - Coreference is a classic IE problem too!
    - More focused response to user need than standard vector space IR
        - Murax, Kupiec, SIGIR 1993; huge amount of recent work

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## Another tool: Summarizing

- High-level summary or survey of all main points?
- How to summarize a collection?
- Example: sentence extraction from a single document (Kupiec et al. 1995; much subsequent work)
  - Start with training set, allows evaluation
  - Create heuristics to identify important sentences:
    - position, IR score, particular discourse cues
  - Classification function estimates the probability a given sentence is included in the abstract
  - 42% average precision

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## IBM Text Miner terminology: Example of Vocabulary found

- Certificate of deposit
- CMOs
- Commercial bank
- Commercial paper
- Commercial Union Assurance
- Commodity Futures Trading Commission
- Consul Restaurant
- Convertible bond
- Credit facility
- Credit line
- Debt security
- Debtor country
- Detroit Edison
- Digital Equipment
- Dollars of debt
- End-March
- Enserch
- Equity warrant
- Eurodollar
- …

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## What is Text Data Mining?

- Peoples' first thought:
  - Make it easier to find things on the Web.
  - But this is information retrieval!
- The metaphor of extracting ore from rock:
  - Does make sense for extracting documents of interest from a huge pile.
  - But does not reflect notions of DM in practice. Rather:
    - finding patterns across large collections
    - discovering heretofore unknown information

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## *Real* Text DM

- What would finding a pattern across a large text collection really look like?
- Discovering heretofore unknown information is not what we usually do with text.
  - (If it weren't known, it could not have been written by someone!)
- However, there is a field whose goal is to learn about patterns in text for its own sake …
- Research that exploits patterns in text does so mainly in the service of computational linguistics, rather than for learning about and exploring text collections.

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## Definitions of Text Mining

- Text mining mainly is about somehow extracting the information and knowledge from text;
- 2 definitions:
  - Any operation related to gathering and analyzing text from external sources for business intelligence purposes;
  - Discovery of knowledge previously unknown to the user in text;
- Text mining is the process of compiling, organizing, and analyzing large document collections to support the delivery of targeted types of information to analysts and decision makers and to discover relationships between related facts that span wide domains of inquiry.

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## TDM using Metadata
### (instead of Text)

- Data:
  - Reuter's newswire (22,000 articles, late 1980s)
  - Categories: commodities, time, countries, people, and topic
- Goals:
  - distributions of categories across time (trends)
  - distributions of categories between collections
  - category co-occurrence (e.g., topic|country)
- Interactive Interface:
  - lists, pie charts, 2D line plots

  - (Dagan, Feldman, and Hirsh, SDAIR '96)

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## True Text Data Mining: Don Swanson's Medical Work

- Given
  - medical titles and abstracts
  - a problem (incurable rare disease)
  - some medical expertise
- find causal links among titles
  - symptoms
  - drugs
  - results
- E.g.: Magnesium deficiency related to migraine
  - This was found by extracting features from medical literature on migraines and nutrition[13]

## Swanson Example (1991)

- Problem: Migraine headaches (M)
  - Stress is associated with migraines;
  - Stress can lead to a loss of magnesium;
  - calcium channel blockers prevent some migraines
  - Magnesium is a natural calcium channel blocker;
  - Spreading cortical depression (SCD) is implicated in some migraines;
  - High levels of magnesium inhibit SCD;
  - Migraine patients have high platelet aggregability;
  - Magnesium can suppress platelet aggregability.
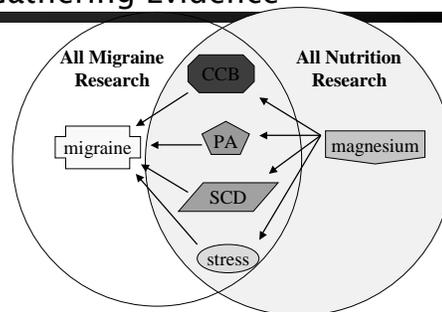- All extracted from medical journal titles

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## Swanson's TDM

- Two of his hypotheses have received some experimental verification.
- His technique
  - Only partially automated
  - Required medical expertise
- Few people are working on this kind of information aggregation problem.

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## Gathering Evidence



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## Or maybe it was already known?



## Extracting Metadata from documents



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## Why metadata?

- Metadata = "data about data"
- "Normalized" semantics
- Enables easy searches otherwise not possible:
  - Time
  - Author
  - Url / filename
- And gives information on non-text content
  - Images
  - Audio
  - Video

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## For Effective Metadata We Need:

- Semantics
  - Commonly understood terms to describe information resources
- Syntax
  - Standard grammar for connecting terms into meaningful "sentences"
- Exchange framework
  - So we can recombine and exchange metadata across applications and subjects

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## Dublin Core Element Set

- Title (e.g., Dublin Core Element Set)
- Creator (e.g., Hinrich Schuetze)
- Subject (e.g, keywords)
- Description (e.g., an abstract)
- Publisher (e.g., Stanford University)
- Contributor (e.g., Chris Manning)
- Date (e.g, 2002.12.03)
- Type (e.g., presentation)
- Format (e.g., ppt)
- Identifier (e.g., http://www.stanford.edu/class/cs276a/syllabus.html)
- Source (e.g. http://dublincore.org/documents/dces/)
- Language (e.g, English)
- Coverage (e.g., San Francisco Bay Area)
- Rights (e.g., Copyright Stanford University)

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## RDF = Resource Description Framework

- Emerging standard for metadata
- W3C standard
  - Part of W3C's metadata framework
- Specialized for WWW
- Desiderata
  - Combine different metadata modules (e.g., different subject areas)
  - Syndication, aggregation, threading

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## RDF example in XML

```
<?xml version="1.0"?> <rdf:RDF
xmlns:rdf="http://www.w3.org/1999/02/22-rdf-syntax-
ns#" xmlns:dc="http://purl.org/dc/elements/1.1/">
<rdf:Description
rdf:about="http://www.ilrt.org/people/cmdjb/">
<dc:title>Dave Beckett's Home Page</dc:title>
<dc:creator>Dave Beckett</dc:creator>
<dc:publisher>ILRT, University of
Bristol</dc:publisher> </rdf:Description> </rdf:RDF>
```
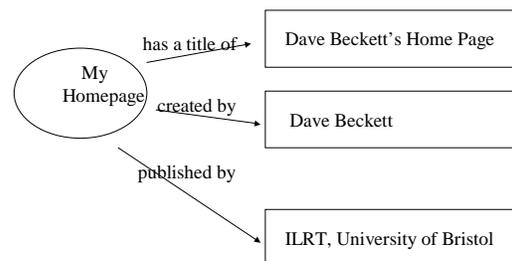
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## RDF example



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## Resource Description Framework (RDF)

- RDF was conceived as a way to wrap metadata assertions (eg Dublin Core information) around a web resource.
- The central concept of the RDF data model is the *triple*, represented as a labeled edge between two nodes.
- The subject, the object, and the predicate are all resources, represented by URIs



http://purl.org/DC/elements/1.1#Creator

http://www.infoloom.com → mailto:mb@infoloom.com
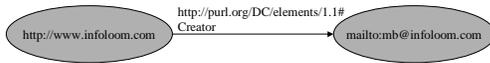
- Properties can be multivalued for a resource, and values can be literals instead of resources
- Graph pieces can be chained and *nested*
- RDF Schema gives frame-based language for ontologies and reasoning over RDF.

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## Metadata Pros and Cons

- CONS
    - Most authors are unwilling to spend time and energy on
        - learning a metadata standard
        - annotating documents they author
    - Authors are unable to foresee all reasons why a document may be interesting.
    - Authors may be motivated to sabotage metadata (patents).
- PROS
    - Information retrieval often does not work.
    - Words poorly approximate meaning.
    - For truly valuable content, it pays to add metadata.
- Synthesis
    - In reality, most documents have some valuable metadata
    - If metadata is available, it improves relevance and user experience
    - But most interesting content will always have inconsistent and spotty metadata coverage

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## Metadata and TextCat/IE

- The claim of metadata proponents is that metadata has to be explicitly annotated, because we can't hope to get, say, a book price from varied documents like:

```
<H1>
<The Rhyme of the Ancient Mariner>
</H1>
<i>The Rhyme of the Ancient Mariner</i>, by Samuel Coleridge, is
available for the low price of $9.99. This Dover reprint is
beautifully illustrated by Gustave Dore.
<p>
Julian Schnabel recently directed a movie, <i>Pandemonium</i>,
about the relationship between Coleridge and Wordsworth.
```

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## Metadata and TextCat/IE

- … but with IE/TextCat, these are exactly the kind of things we *can* do
- Of course, we can do it more accurately with human authored metadata
    - But, of course, the metadata might not match the text (*metadata spamming*)
- Opens up an interesting world where agents use metadata if it's there, but can synthesize it if it isn't (by text cat/IE), and can verify metadata for correctness against text
    - Seems a promising area; not much explored!

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## Lexicon Construction

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## What is a Lexicon?

- A database of the vocabulary of a particular domain (or a language)
- More than a list of words/phrases
- Usually some linguistic information
    - Morphology (manag- e/es/ing/ed -> manage)
    - Syntactic patterns (transitivity etc)
- Often some semantic information
    - Is-a hierarchy
    - Synonymy

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## Lexica in Text Mining

- Many text mining tasks require named entity recognition.
- Named entity recognition requires a lexicon in most cases.
- Example 1: Question answering
  - Where is Mount Everest?
  - A list of geographic locations increases accuracy
- Example 2: Information extraction
  - Consider scraping book data from amazon.com
  - Template contains field "publisher"
  - A list of publishers increases accuracy
- Manual construction is expensive: 1000s of person hours!
- Sometimes an unstructured inventory is sufficient

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## Lexicon Construction (Riloff)

- Attempt 1: Iterative expansion of phrase list
- Start with:
  - Large text corpus
  - List of seed words
- Identify "good" seed word contexts
- Collect close nouns in contexts
- Compute confidence scores for nouns
- Iteratively add high-confidence nouns to seed word list. Go to 2.
- Output: Ranked list of candidates

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## Lexicon Construction: Example

- Category: weapon
- Seed words: bomb, dynamite, explosives
- Context: <new-phrase> and <seed-phrase>
- Iterate:
  - Context: They use TNT and other explosives.
  - Add word: TNT
- Other words added by algorithm: rockets, bombs, missile, arms, bullets

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## Lexicon Construction: Attempt 2

- Multilevel bootstrapping (Riloff and Jones 99)
- Generate two data structures in parallel
  - The lexicon
  - A list of extraction patterns
- Input as before
  - Corpus (not annotated)
  - List of seed words

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## Multilevel Bootstrapping

- Initial lexicon: seed words
- Level 1: Mutual bootstrapping
  - Extraction patterns are learned from lexicon entries.
  - New lexicon entries are learned from extraction patterns
  - Iterate
- Level 2: Filter lexicon
  - Retain only most reliable lexicon entries
  - Go back to level 1
- 2-level performs better than just level 1.

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## Scoring of Patterns

- Example
  - Concept: company
  - Pattern: owned by <x>
- Patterns are scored as follows
  - score(pattern) = F/N log(F)
  - F = number of unique lexicon entries produced by the pattern
  - N = total number of unique phrases produced by the pattern
  - Selects for patterns that are
    - Selective (F/N part)
    - Have a high yield (log(F) part)

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## Scoring of Noun Phrases

- Noun phrases are scored as follows
    - score(NP) = sum_k (1 + 0.01 * score(pattern_k))
    - where we sum over all patterns that fire for NP
    - Main criterion is number of independent patterns that fire for this NP.
    - Give higher score for NPs found by high-confidence patterns.
- Example:
    - New candidate phrase: boeing
    - Occurs in: owned by <x>, sold to <x>,

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## Shallow Parsing

- Shallow parsing needed
    - For identifying noun phrases and their heads
    - For generating extraction patterns
- For scoring, when are two noun phrases the same?
    - Head phrase matching
    - X matches Y if X is the rightmost substring of Y
    - "New Zealand" matches "Eastern New Zealand"
    - "New Zealand cheese" does not match "New Zealand"

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## Seed Words

| | |
|---|---|
| **Web Company:** | *co. company corp. corporation inc. incorporated limited ltd. plc* |
| **Web Location:** | *australia canada china england france germany japan mexico switzerland united_states* |
| **Web Title:** | *ceo cfo president vice-president vp* |
| **Terr. Location:** | *bolivia city colombia district guatemala honduras neighborhood nicaragua region town* |
| **Terr. Weapon:** | *bomb bombs dynamite explosive explosives gun guns rifle rifles tnt* |

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## Mutual Bootstrapping

Generate all candidate extraction patterns from the training corpus using AutoSlog.

Apply the candidate extraction patterns to the training corpus and save the patterns with their extractions to *EPdata*

*SemLex* = {seed_words}

*Cat_EPlist* = {}

MUTUAL BOOTSTRAPPING LOOP

1. Score all extraction patterns in *EPdata*.
2. *best_EP* = the highest scoring extraction pattern not already in *Cat_EPlist*.
3. Add *best_EP* to *Cat_EPlist*
4. Add *best_EP*'s extractions to *SemLex*.
5. Go to step 1

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## Extraction Patterns

| Web Company Patterns |
|---|
| owned by <x> |
| both as <x> |
| <x> employed |
| <x> is distributor |
| <x> positioning |
| marks of <x> |
| motivated <x> |
| <x> trust company |
| sold to <x> |
| devoted to <x> |
| <x> consolidated stmts. |
| <x> thrive |
| message to <x> |
| <x> is obligations |
| <x> request information |
| <x> is foundation |
| <x> has positions |
| incorporated as <x> |
| offices of <x> |
| <x> required to meet |

## Level 1: Mutual Bootstrapping

| | |
|---|---|
| Best pattern | "headquartered in <x>" (F=3,N=4) |
| Known locations | *nicaragua* |
| New locations | *san miguel, chapare region, san miguel city* |
| Best pattern | "gripped <x>" (F=2,N=2) |
| Known locations | *colombia, guatemala* |
| New locations | *none* |
| Best pattern | "downed in <x>" (F=3,N=6) |
| Known locations | *nicaragua, san miguel*, city* |
| New locations | *area, usulutan region, soyapango* |
| Best pattern | "to occupy <x>" (F=4,N=6) |
| Known locations | *nicaragua, town* |
| New locations | *small country, this northern area, san sebastian neighborhood, private property* |
| Best pattern | "shot in <x>" (F=5,N=12) |
| Known locations | *city, soyapango** |
| New locations | *jauja, central square, head, clash, back, central mountain region, air, villa el salvador district, northwestern guatemala, left side* |

- Drift can occur.
- It only takes one bad apple to spoil the barrel.
- Example: head
- Introduce level 2 bootstrapping to prevent drift.

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## Level 2: Meta-Bootstrapping



META-BOOTSTRAPPING

- candidate extraction patterns & their extractions
- seed words
- MUTUAL BOOTSTRAPPING
- permanent semantic lexicon
- *initialize*
- temporary semantic lexicon
- *select best_EP*
- category EP list
- *add 5 best NPs*
- *add best_EP's extractions*
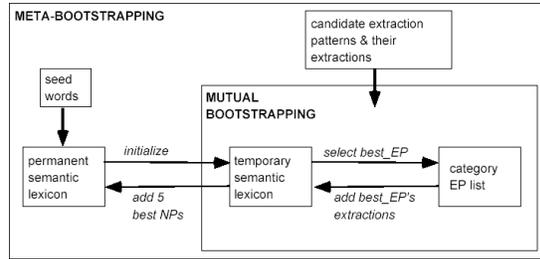
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## Evaluation

| Recall/Precision (%) | Baseline | Lexicon | Union |
|---|---|---|---|
| Web Company | 10/32 | 18/47 | 18/45 |
| Web Location | 11/98 | 51/77 | 54/74 |
| Web Title | 6/100 | 46/66 | 47/62 |

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## Collins&Singer: CoTraining

- Similar back and forth between
  - an extraction algorithm and
  - a lexicon
- New: They use word-internal features
  - Is the word all caps? (IBM)
  - Is the word all caps with at least one period? (N.Y.)
  - Non-alphabetic character? (AT&T)
  - The constituent words of the phrase ("Bill" is a feature of the phrase "Bill Clinton")
- Classification formalism: Decision Lists

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## Collins&Singer: Seed Words

```
full-string=New_York      →     Location
full-string=California    →     Location
full-string=U.S.          →     Location
contains(Mr.)             →     Person
contains(Incorporated)    →     Organization
full-string=Microsoft     →     Organization
full-string=I.B.M.        →     Organization
```

Note that categories are more generic than in the case of Riloff/Jones.

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## Collins&Singer: Algorithm

- Train decision rules on current lexicon (initially: seed words).
  - Result: new set of decision rules.
- Apply decision rules to training set
  - Result: new lexicon
- Repeat

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## Collins&Singer: Results

| Learning Algorithm | Accuracy (Clean) | Accuracy (Noise) |
|---|---|---|
| Baseline | 45.8% | 41.8% |
| EM | 83.1% | 75.8% |
| (Yarowsky 95) | 81.3% | 74.1% |
| **Yarowsky-cautious** | 91.2% | 83.2% |
| **DL-CoTrain** | 91.3% | 83.3% |
| **CoBoost** | 91.1% | 83.1% |

Per-token evaluation?

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## Lexica: Limitations

- Named entity recognition is more than lookup in a list.
- Linguistic variation
  - Manage, manages, managed, managing
- Non-linguistic variation
  - Human gene MYH6 in lexicon, MYH7 in text
- Ambiguity
  - What if a phrase has two different semantic classes?
  - Bioinformatics example: gene/protein metonymy

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## Lexica: Limitations - Ambiguity

- Metonymy is a widespread source of ambiguity.
- Metonymy: A figure of speech in which one word or phrase is substituted for another with which it is closely associated. (king – crown)
- Gene/protein metonymy
  - The gene name is often used for its protein product.
  - TIMP1 inhibits the HIV protease.
  - TIMP1 could be a gene or protein.
  - Important difference if you are searching for TIMP1 protein/protein interactions.
- Some form of disambiguation necessary to identify correct sense.

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## Discussion

Partial resources often available.
  - E.g., you have a gazetteer, you want to extend it to a new geographic area.
- Some manual post-editing necessary for high-quality.
- Semi-automated approaches offer good coverage with much reduced human effort.
- Drift not a problem in practice if there is a human in the loop anyway.
- Approach that can deal with diverse evidence preferable.
- Hand-crafted features (period for "N.Y.") help a lot.

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## Terminology Acquisition

- Goal: find heretofore unknown noun phrases in a text corpus (similar to lexicon construction)
- Lexicon construction
  - Emphasis on finding noun phrases in a specific semantic class (companies)
  - Application: Information extraction
- Terminology Acquisition
  - Emphasis on term normalization (e.g., viral and bacterial infections -> viral_infection)
  - Applications: translation dictionaries, information retrieval

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## Lexica For Research Index

- Lexica of which classes would be useful?

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