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Information Retrieval

by

Dr. Rajendra Prasath

Indian Institute of Information Technology

Sri City – 517 646, Andhra Pradesh, India

Lecture – 08

✧ Topics Covered So Far

- ✧ Bi-Word Index
- ✧ Wild Card Queries
- ✧ Permuterm Index
- ✧ K-gram Index (k = 2 → Bigram Index)
- ✧ Spell Correction

✧ Now: Term Weighting

- ✧ Approaches to terms weighting in IR

Recap: Spelling Tasks

- ✧ Spelling Error Detection
- ✧ Spelling Error Correction:
  - ✧ Autocorrect
    - ✧ hte→the
  - ✧ Suggest a correction
  - ✧ Suggestion lists

Recap: Real word & non-word spelling errors

- For each word *w*, generate candidate set:
  - Find candidate words with similar ***pronunciations***
  - Find candidate words with similar ***spellings***
  - Include *w* in candidate set
- Choose best candidate
  - Noisy Channel view of spell errors
  - Context-sensitive – so have to consider whether the surrounding words "make sense"
  - *Flying* **form** *Heathrow to LAX* → *Flying* **from** *Heathrow to LAX*

Recap: Language Model

- Take a big supply of words (your document collection with T tokens); let C(w) = # occurrences of w

$$P(w) = \frac{C(w)}{T}$$

- In other applications – you can take the supply to be typed queries (suitably filtered) – when a static dictionary is inadequate

Recap: Channel model

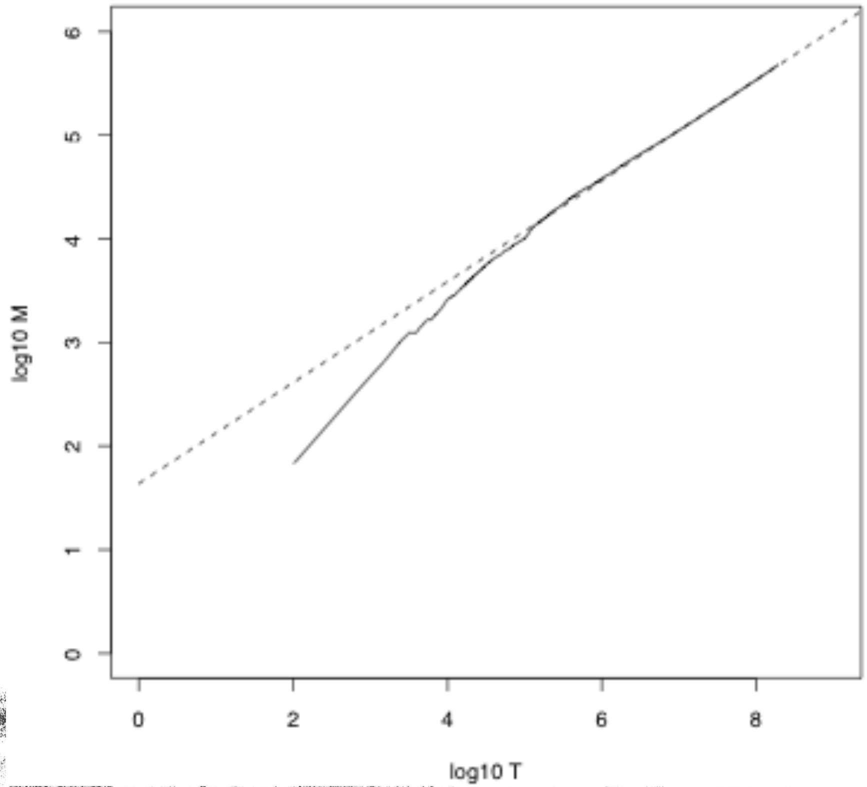
$$P(x|w) = \begin{cases} \dfrac{\text{del}[w_{i-1}, w_i]}{\text{count}[w_{i-1} w_i]}, & \text{if deletion} \\ \dfrac{\text{ins}[w_{i-1}, x_i]}{\text{count}[w_{i-1}]}, & \text{if insertion} \\ \dfrac{\text{sub}[x_i, w_i]}{\text{count}[w_i]}, & \text{if substitution} \\ \dfrac{\text{trans}[w_i, w_{i+1}]}{\text{count}[w_i w_{i+1}]}, & \text{if transposition} \end{cases}$$

Kernighan, Church, Gale 1990

Overview

- Why ranked retrieval?
- Term frequency
- tf-idf weighting
- The vector space model

Heaps' law



Vocabulary size M as a function of collection size T (number of tokens) for Reuters-RCV1. For these data, the dashed line $\log_{10} M = 0.49 * \log_{10} T + 1.64$ is the best least squares fit. Thus, $M = 10^{1.64} T^{0.49}$ and $k = 10^{1.64} \approx 44$ and $b = 0.49$.

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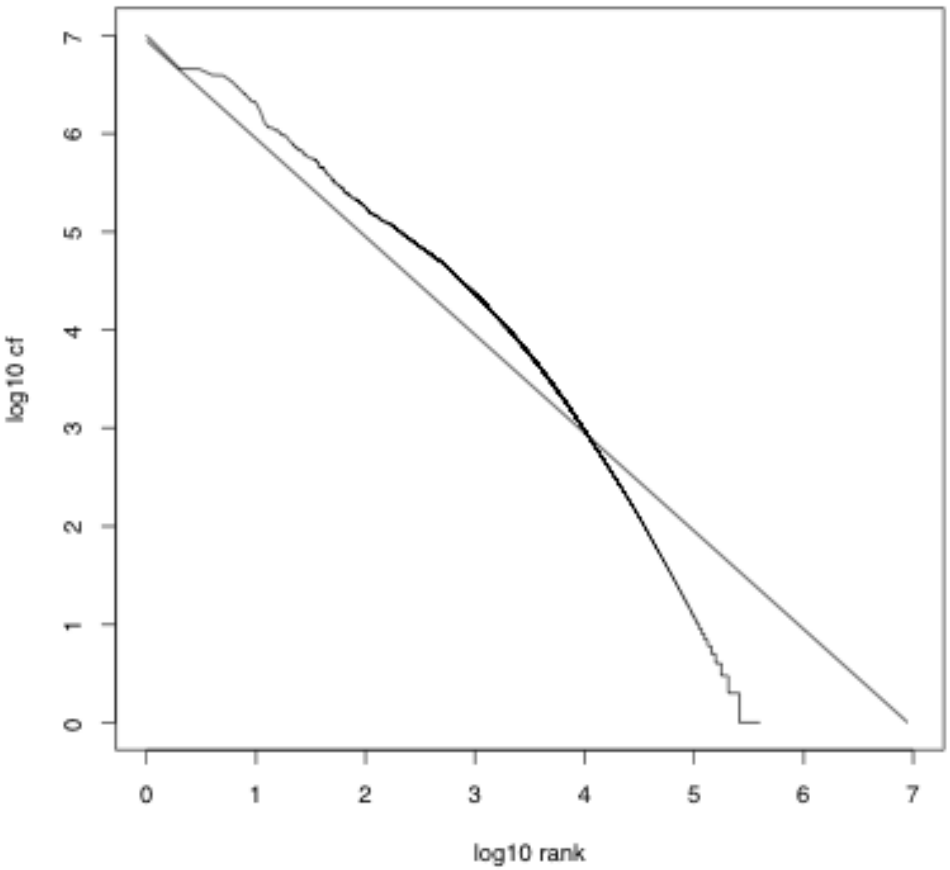
Zipf's law



$\mathrm{cf}_i \propto \frac{1}{i}$

The most frequent term (*the*) occurs cf_1 times, the second most frequent term (*of*) occurs $\mathrm{cf}_2 = \frac{1}{2}\mathrm{cf}_1$ times, the third most frequent term (*and*) occurs $\mathrm{cf}_3 = \frac{1}{3}\mathrm{cf}_1$ times etc.

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Ranked Retrieval

- Our Queries have all been Boolean
  - Documents either match or don't
- Good for expert users with precise understanding of their needs and of the collection.
- Also good for applications: Applications can easily consume 1000s of results.
- Not good for the majority of users
- Most users don't want to wade through 1000s of results.
- This is particularly true of web search.

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Problem with Boolean search: Feast or famine

- Boolean queries often result in either too few (=0) or too many (1000s) results.
- Query 1 (boolean conjunction): [standard user dlink 650]
  - → 200,000 hits – feast
- Query 2 (boolean conjunction): [standard user dlink 650 no card found]
  - → 0 hits – famine
- In Boolean retrieval, it takes a lot of skill to come up with a query that produces a manageable number of hits.

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Feast or famine: No problem in ranked retrieval

- With ranking, large result sets are not an issue
- Just show the top 10 results
- Does not overwhelm the user
- Premise: the ranking algorithm works: More relevant results are ranked higher than less relevant results.

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Scoring as the basis of ranked retrieval

- ✧ We wish to rank documents that are more relevant higher than documents that are less relevant.
- ✧ How can we accomplish such a ranking of the documents in the collection with respect to a query?
- ✧ Assign a score to each query-document pair, say in [0, 1]
- ✧ This score measures how well document and query "match"

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Query-document matching scores

- How do we compute the score of a query-document pair?
- Let's start with a one-term query.
- If the query term does not occur in the document: score should be 0.
- The more frequent the query term in the document, the higher the score
- We will look at a number of alternatives for doing this.

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Jaccard coefficient

- A commonly used measure of overlap of two sets
- Let A and B be two sets
- Jaccard coefficient:

$$\textsc{Jaccard}(A,B) = \frac{|A \cap B|}{|A \cup B|}$$

$(A \neq \emptyset$ or $B \neq \emptyset)$

- JACCARD (A, A) = 1
- JACCARD (A, B) = 0 if $A \cap B = 0$
- A and B don't have to be the same size.
- Always assigns a number between 0 and 1.

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Jaccard coefficient: Example

- What is the query-document match score that the Jaccard coefficient computes for:
  - Query: “ides of March”
  - Document “Caesar died in March”
  - JACCARD(q, d) = 1/6

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What's wrong with Jaccard?

- It does not consider term frequency (how many occurrences a term has)
- Rare terms are more informative than frequent terms
  - Jaccard does not consider this information
- We need a more sophisticated way of normalizing the length of a document

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Binary incidence matrix

	Anthony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth . . .
ANTHONY	1	1	0	0	0	1
BRUTUS	1	1	0	1	0	0
CAESAR	1	1	0	1	1	1
CALPURNIA	0	1	0	0	0	0
CLEOPATRA	1	0	0	0	0	0
MERCY	1	0	1	1	1	1
WORSER	1	0	1	1	1	0
. . .						

Each document is represented as a binary vector $\in \{0, 1\}^{|V|}$.

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Binary incidence matrix

	Anthony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth . . .
ANTHONY	157	73	0	0	0	1
BRUTUS	4	157	0	2	0	0
CAESAR	232	227	0	2	1	0
CALPURNIA	0	10	0	0	0	0
CLEOPATRA	57	0	0	0	0	0
MERCY	2	0	3	8	5	8
WORSER	2	0	1	1	1	5
. . .						

Each document is now represented as a count vector $\in \mathbb{N}^{|V|}$.

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Bag of words model

- ✧ We do not consider the order of words in a document.
- ✧ John is quicker than Mary and Mary is quicker than John are represented the same way.
- ✧ This is called a bag of words model.
- ✧ In a sense, this is a step back: The positional index was able to distinguish these two documents.
- ✧ We will look at “recovering” positional information later in this course.
- ✧ For now: bag of words model

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Term frequency (tf)

- ✧ The term frequency tft,d of term t in document d is defined as the number of times that t occurs in d
- ✧ Use tf to compute query-doc. match scores
- ✧ Raw term frequency is not what we want
- ✧ A document with tf = 10 occurrences of the term is more relevant than a document with tf = 1 occurrence of the term
- ✧ But not 10 times more relevant
- ✧ Relevance does not increase proportionally with term frequency

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Log frequency weighting

- The log frequency weight of term t in d is defined as follows

$$w_{t,d} = \begin{cases} 1 + \log_{10} \mathrm{tf}_{t,d} & \text{if } \mathrm{tf}_{t,d} > 0 \\ 0 & \text{otherwise} \end{cases}$$

- $tf_{t,d} \rightarrow w_{t,d}$:
  $0 \rightarrow 0$, $1 \rightarrow 1$, $2 \rightarrow 1.3$, $10 \rightarrow 2$, $1000 \rightarrow 4$, etc.
- Score for a document-query pair: sum over terms t in both q and d:
  $$\text{tf-matching-score}(q, d) = \sum_{t \in q \cap d} (1 + \log tf_{t,d})$$

- The score is 0 if none of the query terms is present in the document

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Exercise

- Compute Jaccard matching score & TF matching score for the following query-document pairs

- q: [information on cars]

  d: “all you’ve ever wanted to know about cars”
- q: [information on cars]

  d: “information on trucks, information on planes, information on trains”
- q: [red cars and red trucks]

  d: “cops stop red cars more often”

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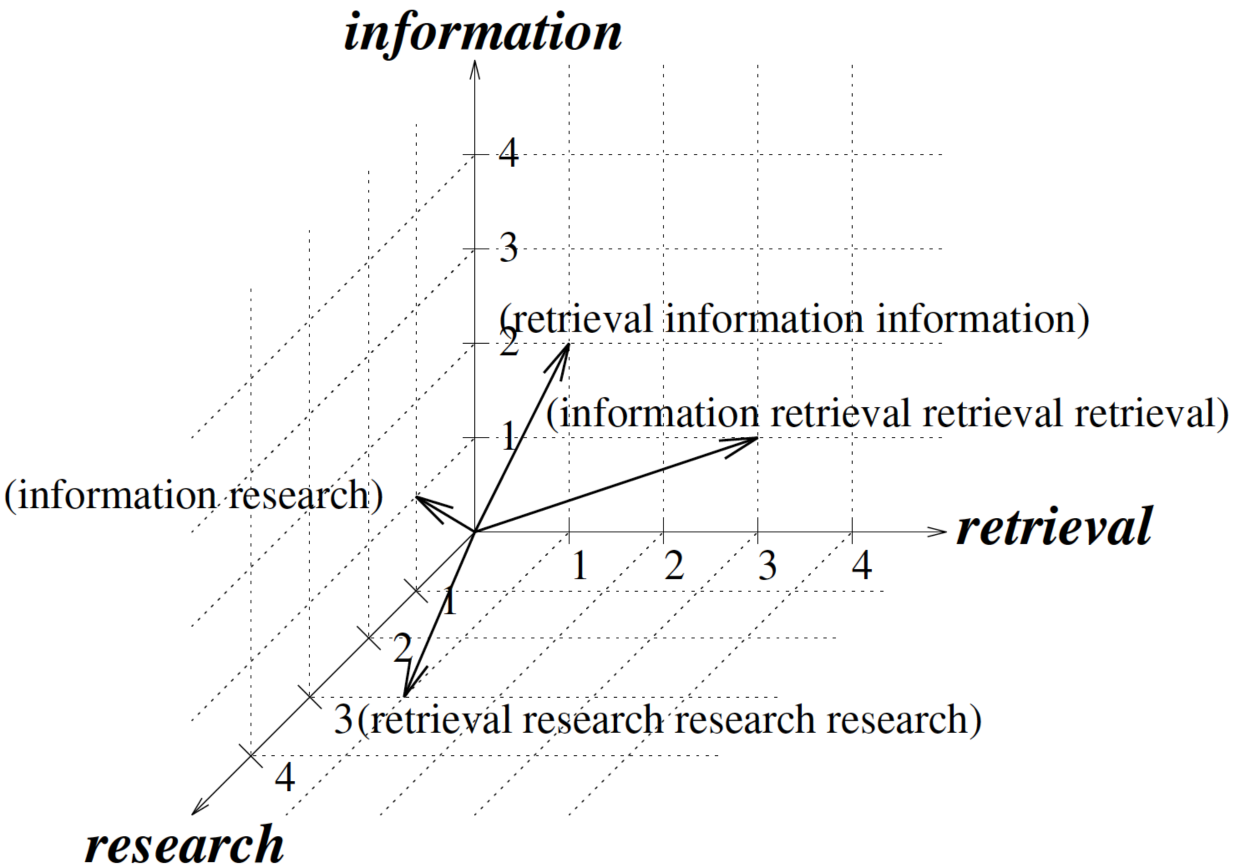
Vector Space Model

- Consider three word model
  "information retrieval research"



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Measure of Closeness of Vectors

- How to measure the closeness between two vectors (texts)?
- Two texts are semantically related if they share some vocabulary
  - More Vocabulary they share, the stronger is the relationship
- This implies that the measure of closeness increases with the number of words matches between two texts
- If matching terms are important then the vectors should be considered closer to each other

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Modern Vector Space Models

- The length of the sub-vector in dimension-i is used to represent the importance or the weigh of word-i in a text
- Words that are absent in a text get a weight – 0 (zero)
- Apply *vector inner product* measure between two vectors:
- This vector inner product increases:
  - # words match between two texts
  - Importance of the matching terms

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Finding closeness between texts

- Given two texts in T dimensional vector space:

$$\vec{P} = (p_1, p_2, \ldots, p_T) \text{ and } \vec{Q} = (q_1, q_2, \ldots, q_T)$$

- The inner product between these two vectors:

$$\vec{P} \cdot \vec{Q} = \sum_{i=1}^{T} \sum_{j=1}^{T} p_i \times \vec{u_i} \cdot q_j \times \vec{u_j}$$

- Vectors u_i and u_j are unit vectors in dimensions *i and j* (Here $u_i \bullet u_j = 0$, if $i \neq j$ - orthogonal)
- Vector Similarity: Closeness between two texts

$$similarity(\vec{P}, \vec{Q}) = \sum_{i=1}^{T} p_i \times q_i$$

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Term Weighting

- The Importance of a term increases with the number of occurrences of a term in a text.

- So we can estimate the term weight using some monotonically increasing function of the number of occurrences of a term in a text

- **Term Frequency:**

  The number of occurrences of a term in a text is called **Term Frequency**

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Term Frequency Factor

- What is Term Frequency Factor?
  - The function of the term frequency used to compute a term's importance
  - Some commonly used factors are:
    - Raw TF factor
    - Logarithmic TF factor
    - Binary TF factor
    - Augmented TF factor
    - Okapi's TF factor

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The Raw TF factor

- This is the simplest factor
- This counts simply the number of occurrences of a term in a text
- Simply count the number of terms in each document
- More the number, higher the ranking of the document!!

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The Logarithmic TF factor

- This factor is computed as

  $$1 + \ln(tf)$$

  where tf is the term frequency of a term
- Proposed by Buckley (1993 - 94)
- Motivation:
  - If a document has one query term with a very high term frequency then the document is (often) not better than another document that has two query terms with somewhat lower term frequencies
  - More occurrences of a match should not out-contribute fewer occurrences of several matches

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Example – log TF factor

- Consider the query: “recycling of tires”
- Two documents:

D1: with 10 occurrences of the word “recycling”

D2: with “recycling” and “tires” 3 times each

- Everything else being equal, if we use raw tf, D1(10) gets higher similarity score than D2 (3+3=6)
- But D2 addresses the needs of the query
- Log TF: reflects usefulness of D2 in similarities
- D1: $1 + \ln(10) = 3.3$ and D2: $2(1+\ln(3)) = 4.1$

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The Binary TF factor

- The TF factor is completely disregards the number of occurrences of a term.
- It is either one or zero depending upon the presence (one) or the absence (zero) of the term in a text.
- This factor gives a nice baseline to measure the usefulness of the term frequency factors in document ranking

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The Augmented TF factor

- This TF factor reduces the range of the contributions of a term from the freq. of a term
- How: Compress the range of the possible TF factor values (say between 0.5 & 1.0)
- The augmented TF factor is used with a belief that mere presence of a term in a text should have some default weight (say 0.5)
- Then additional occurrences of a term could increase the weight of the term to some max. value (usually 1.0).

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Augmented TF factor - Scoring

- This TF factor is computed as follows:

$$0.5 + 0.5 \times \frac{tf}{\text{maximum tf in text}}$$

- The augmented TF factor emphasizes that more matches are more importance than fewer matches (like log TF factor)
- A single match contributes at least 0.5 and high TFs can only contribute at most another 0.5
- This was motivated by document length considerations and does not work as well as log TF factor in practice.

Okapi's TF factor

- Robertson et. Al (1994) developed Okapi Information Retrieval System and proposed another TF factor
- This TF factor is based on Approximations to the 2-Poossion Model:
- This factor $$\frac{tf}{2 + tf}$$

  is quite close to the log TF factor in its behavior
- In practice, log TF factor is effective for good document ranking

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Exercise – E08

- Consider a collection of n documents
- Let n be sufficiently large (at least 100 docs)
- Find two lists:
  - The most frequency words and
  - The least frequent words
- Form k (=10) queries each with exactly 3-words taken from above lists (at least one from each)
- Compute Similarity between each query and and documents

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Summary

In this class, we focused on:

(a) Words / Terms / Lexical Units

(b) Term Weighting approaches

(c) Evaluating the best term weighting approach

Acknowledgements

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2. Search Engines Information Retrieval in Practice W. Bruce Croft, D. Metzler, T. Strohman, Pearson, 2009.
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4. Modern Information Retrieval Baeza-Yates and Ribeiro-Neto, Addison Wesley, 1999.
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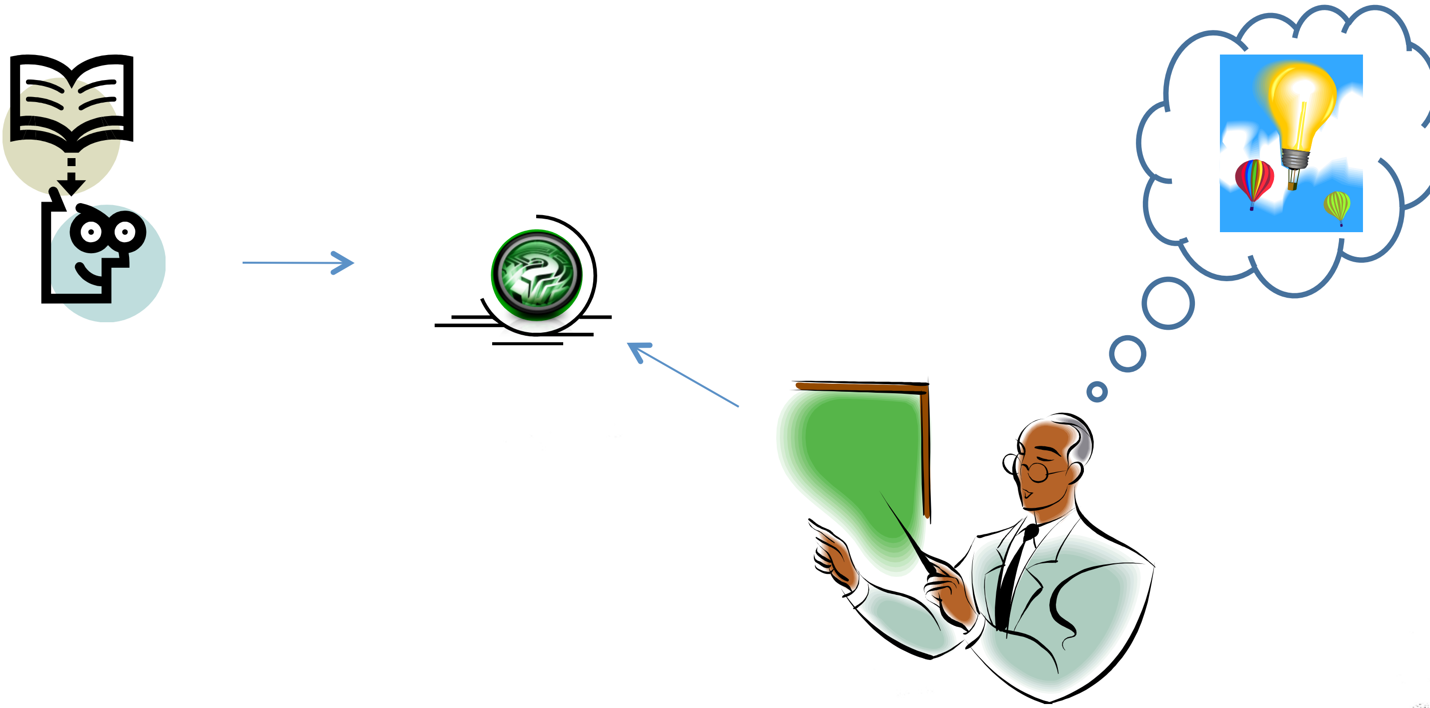

… Questions ???