An evaluation model for systems and resources involved in the correction of errors in textual documents

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Context & Issues

- **Information production process evolution leads to errors**

- **How to manage errors in IR systems ?**

  - **Errors in queries:**
    - → Suggestions of more likely queries through « Did you mean… »

  - **Errors in documents:**
    - → Queries expansion
      - *Expand queries with keywords variations standing for errors expected to lie in documents*
    - → Documents error processing
      - *Correction of errors directly in processed documents*
      - *Seems to be the best fitted one according to [Kantor'00]*

- **How to evaluate error correction systems ?**

Outline

State of the art
- Types of errors & classification
- Error correction approaches
- Error correction evaluation limits

Proposal
- Generic Evaluation Model (Meta-Model)
- Specific Evaluation Model (Model)

Evaluation
- Evaluation model implementation
- Instantiation & analysis of evaluation model resources
- Results

Conclusion & further works

Types of errors & classification (1/2)

Non-word:

- **Invalid word according to a lexicon.**
- **Example:**

  « The bok is on the table. »

  - The word « *bok* » doesn't exist in English and probably comes from mistyping the word « *bo~~o~~k* ».
  - The sentence should be: « *The book is on the table.* ».

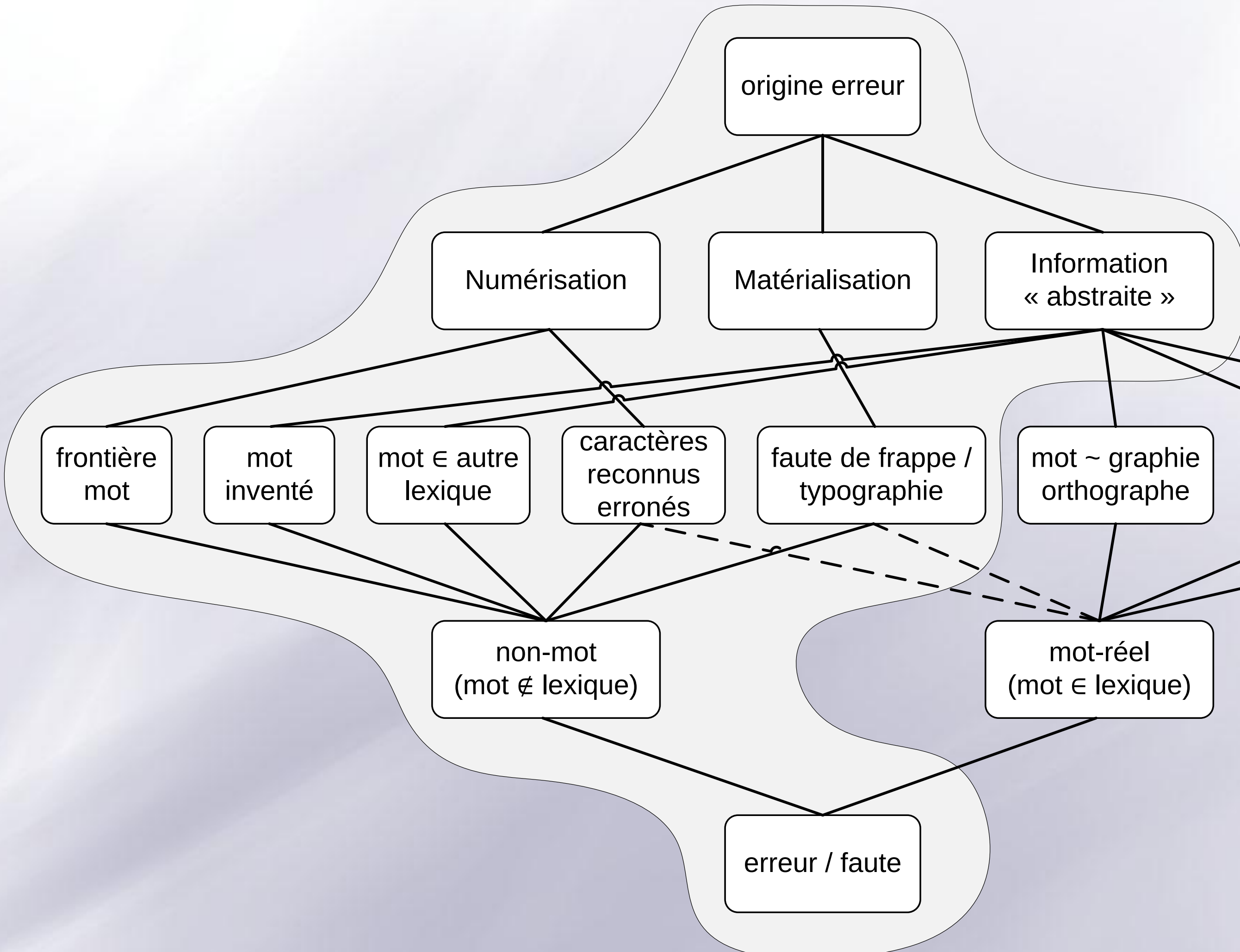
Real-word:

- **Valid word according to a lexicon but not the intended word.**
- **Example:**

  « I saw tree trees in the park. »

  - The word « *tree* » exists in English but doesn't mean anything in this context so it probably comes from mistyping the word « *t~~h~~ree* ».
  - The sentence should be: « *I saw three trees in the park.* ».

Types of errors & classification (2/2)



- **Erreurs mots-réels → plutôt liées à l'information « abstraite »**
- **Erreurs non-mots → plutôt liées à la matérialisation / numérisation de l'information**

Error correction approaches

Semantic based approaches

- **Intuition [Hirst'98, Hirst'05]:**
  - Intended words are generally semantically related to close words which constitute the context
  - Real-word errors brake the semantics
  - Application of semantic disambiguation methods to correct errors
- **Constraints:** context + needs semantic resource

Statistic based approaches

- **Without context [Mitton'09]: simple word frequency**
  - 84% of correct words belongs to most frequent words [Pedler'07]
  - 62% of errors belongs to less frequent words [Pedler'07]
- **With context: statistics on words co-occurence (n-grams)**
  - Trigram presence in a large corpus of documents (BNC) [Verberne'02]
  - Trigram probabilities [Mays'91]
  - N-grams probabilities [Golding'99], [Islam'09] trained over Google Web 1-T n-grams)
- **Constraints:** context + learning phase

Error correction evaluation limits

Different approaches are difficult to compare each other [Wilcox'08]

- **Different resources involved**
  - Reference dictionaries
  - Error collections (randomly generated errors in a pre-existing collection of documents)
    - *Is it representative ?*
    - *Is it reproducible ?*
  - Evaluation metrics
  - Autonomous error correction systems (black boxes services)

- **Elements to address this issue**
  - Gather and distribute collection of real documents which contains errors [Pedler, 2007]
  - Implement previous approaches at the same time to have similar experiment conditions [Wilcox, 2008]

→ **Standard evaluation model to use to evaluate error corrections systems in the same way.**

Proposal (1/4): Evaluation model

Why:

- **Formalize an evaluation framework**
  - Inspired by Cranfield [Cloverdon'60, Cloverdon'66] → TREC, INEX, …
- **Evaluation:**
  - **composites systems**: open systems created from an original resources combination
  - **autonomous systems**: closed systems which can be seen as black boxes

3 levels:

- **Meta-model (Generic Evaluation Model GEM)**
  - Defines different resources types
- **Model adapted to evaluate error correction systems (Specific Evaluation Model SEM)**
  - Derived from GEM
  - Defines families of resources for each type
- **Instantiation of model resources**

Proposal (2/4) : GEM (Meta-model)

Generic Evaluation Model:

$$GEM = \langle R_D, R_P, s, R_E, a \rangle$$

- **R_D: data resources**
  - Example : data to process
- **R_P: processing resources**
  - Example: algorithms to apply to data
- **R_E: evaluation resources**
  - Example: evaluation metrics, reference values
- **s: data processing module based on provided resources R to produce results**
  - Example: scores
- **a: module to evaluate data processing s results and produce performance indicators**
  - Example: recall, precision, MRR, …

Proposal (3/4): SEM (Model)

Specific Evaluation Model:

- **Composites Systems evaluation:**

$$SEM_{composite} = \langle \{Coll, Dict\}, SDM, s, EM, a \rangle$$

- **R_D: data resources**
  - $Coll$: Error collection (list of pairs of the form: $\langle wrong\ word, target\ word \rangle$)
  - $Dict$: Reference dictionary (list of the form: $\langle word, word\ frequency \rangle$)

- **R_P: data processing resources**
  - SDM: Similarity and Distance Measures normalized [0, 1]
  - AS: Autonomous System

- **R_E: evaluation resources**
  - EM: Evaluation Metrics

Proposal (4/4): SEM (Model)

Specific Evaluation Model

- **Autonomous Systems evaluation:**

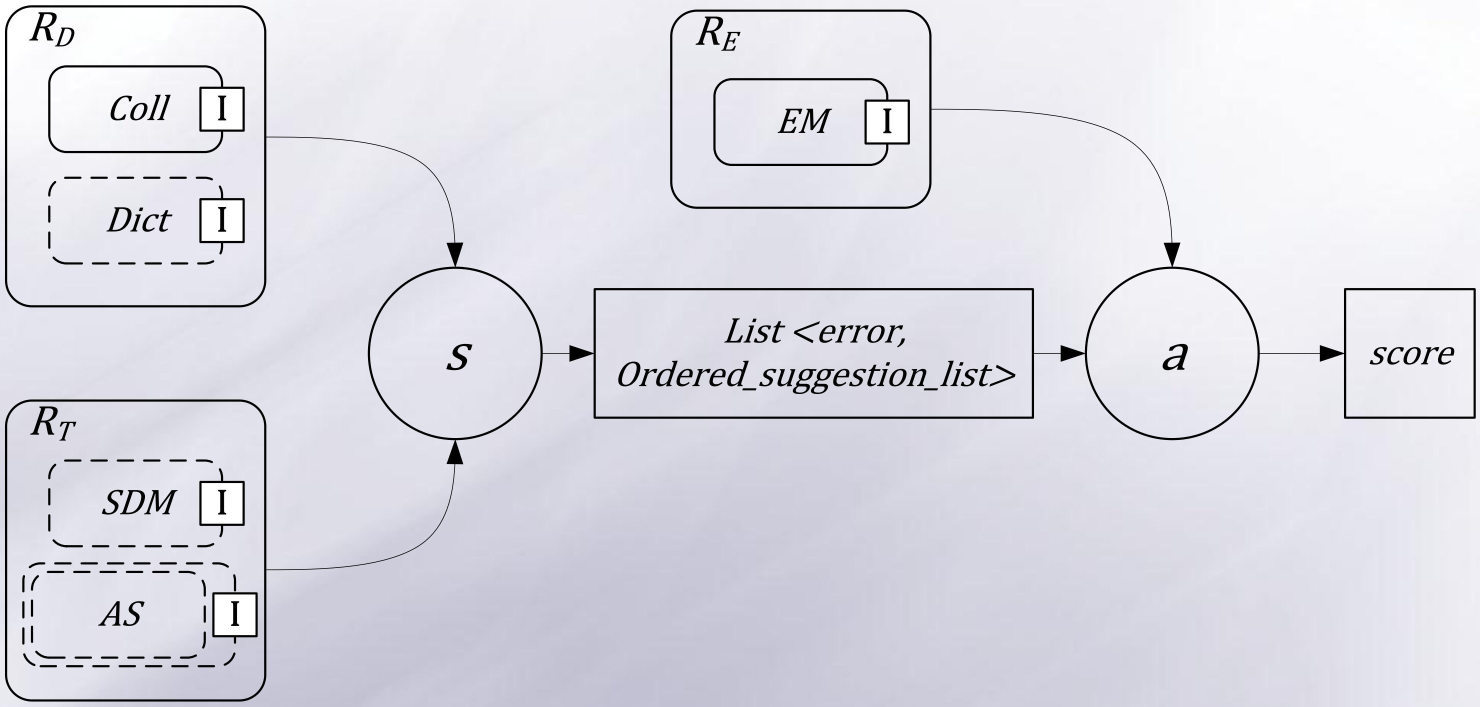
$$SEM_{autonomous} = \langle \{Coll\}, AS, s, EM, a \rangle$$

- **R_D: data resources**
  - $Coll$: Error collection (list of pairs of the form: $\langle wrong\ word, target\ word \rangle$)
  - $Dict$: Reference dictionary (list of the form: $\langle word, word\ frequency \rangle$)

- **R_P: data processing resources**
  - SDM: Similarity and Distance Measures normalized [0, 1]
  - AS: Autonomous System

- **R_E: evaluation resources**
  - EM: Evaluation Metrics

Evaluation (1) : Model implementation



- **Standard interface for every type of resources which are implemented by one or many OSGi bundles**
- **Easy to substitute one bundle with another while they are supposed to have the same type (ex: replace one similarity/distance measure with another one)**

Evaluation (2) : Resources instantiation

Errors collection:

- **WCM Wikipedia Common Misspellings [Wikipedia'10]**
  - **Built from frequent Wikipedia contributors errors**
  - **4274 couples** $< wrong\ word, target\ word >$
  - **Both non-word and real-word errors**
    - *No provided context but errors already identified*

Evaluation (3) : Resources instantiation

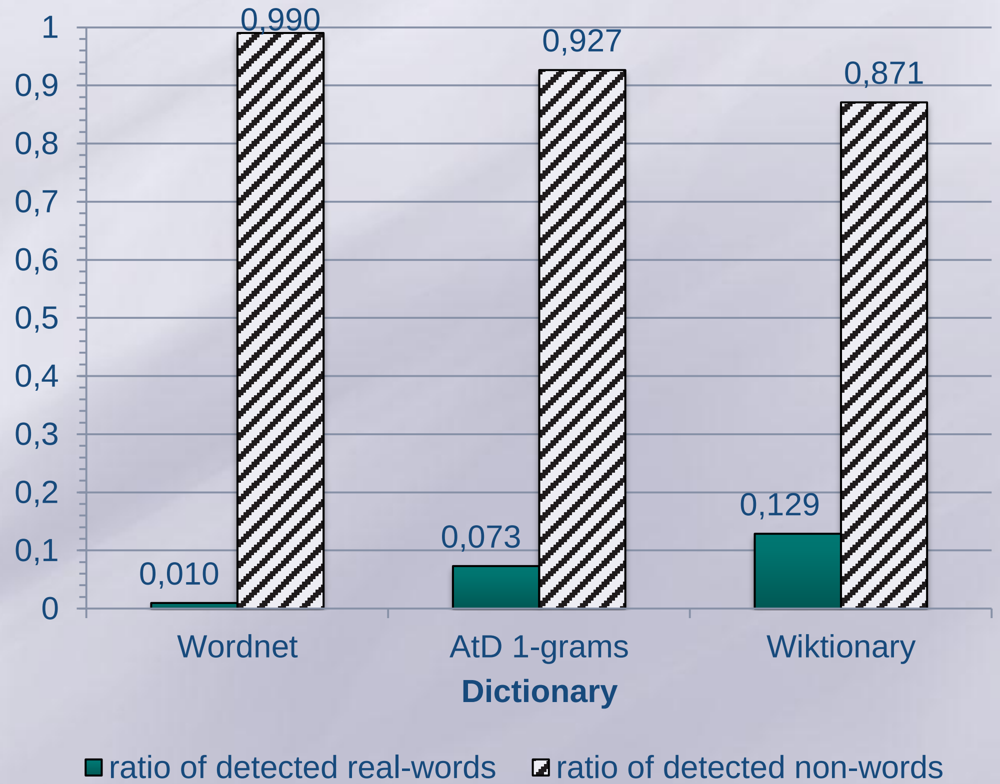
Dictionaries :

- **Wordnet [Miller'95] [Fellbaum'98]**
  - Semantic resource employed as a lexical database
  - Number of words: 147 000 words
- **AtD Unigrams [AtD'10]**
  - Learning of most frequent unigrams on a large document dataset
  - Number of words: 165 000 words
- **Wiktionary [Wiktionary'10]**
  - Online collaborative dictionary → evolves continuously
  - Number of words: 2 000 000 words

Evaluation (4) : Resources analysis

Dictionaries :

- Proportion of words in the collection which identified as real-words errors (resp. non-words) according to the dictionary.

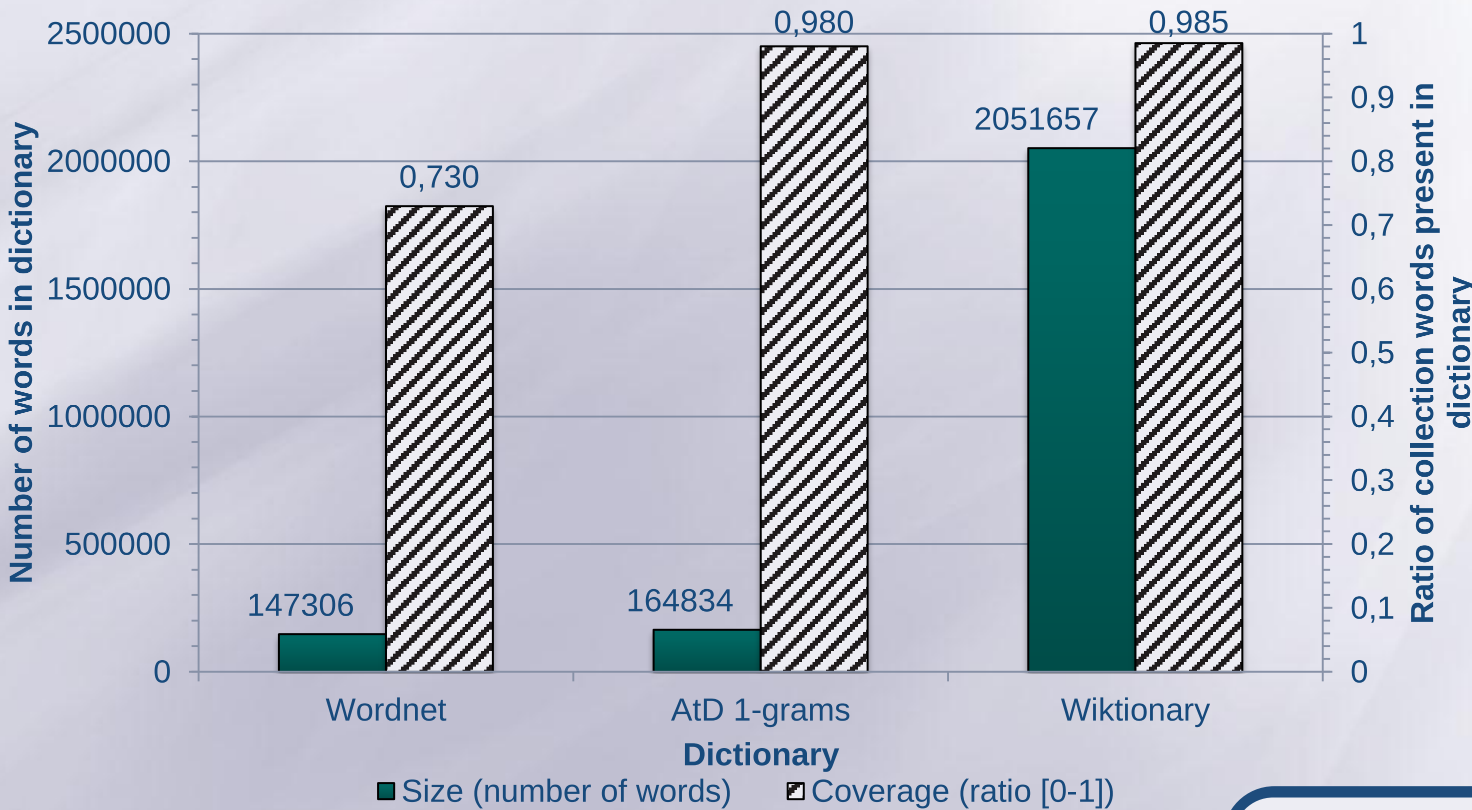


- Dependent of the dictionary
- Temporal evolution (new/old words)

Evaluation (5) : Resources analysis

Dictionaries :

- Dictionaries size and collection of errors target words coverage.



Evaluation (6) : Resources instantiation

Similarity / distance measures

- **Levenshtein distance (edit distance)**
  - Minimal number of characters to delete, insert or substitute to transform a word in an another word.
- **Jaro distance**
  - Based on the number of matching characters between two strings.
  - Two characters can be considered as matching if their positions in the words are not too far from each other (maximum distance threshold).
- **Jaro-Winkler distance**
  - Same as Jaro distance but strings having similar prefixes are favoured.

Evaluation (7) : Resources instantiation

Evaluation metric

- **Integrate an error correction system to an IR system**
- **Constraint: same as offline error correction systems**
  →No user interactions

	Online error correction (standard)	Offline error correction (ITEC)
Contextual data	Yes: directly usable	No: metadata → assumptions
User interactions	Yes: choice among many suggestions (≈ 5)	No: no choice → high precision required

Evaluation (8) : Resources Instantiation

Evaluation metric

- **Precision oriented error correction system**
  - Correct result in first position

    → Appropriate metric: $MRR\ (Mean\ Reciprocal\ Rank)$

$$MRR = \frac{1}{|errorsCouples|} \sum_{i=1}^{|errorsCouple|} \frac{1}{rank_{FoundTagetWord}}$$

  - MRR applies a huge penalty when the good result is not ranked first (divide by the rank)

Evaluation (9) : Synthesis

Instantiation (EMI) of SEM's resources

$$EMI_1 = \langle \{WCM, Wiktionary\}, Jaro - Winkler, s, MRR, e \rangle$$

$$EMI_2 = \langle \{WCM, Wiktionary\}, Jaro, s, MRR, e \rangle$$

$$EMI_3 = \langle \{WCM, Wiktionary\}, Levenshtein, s, MRR, e \rangle$$

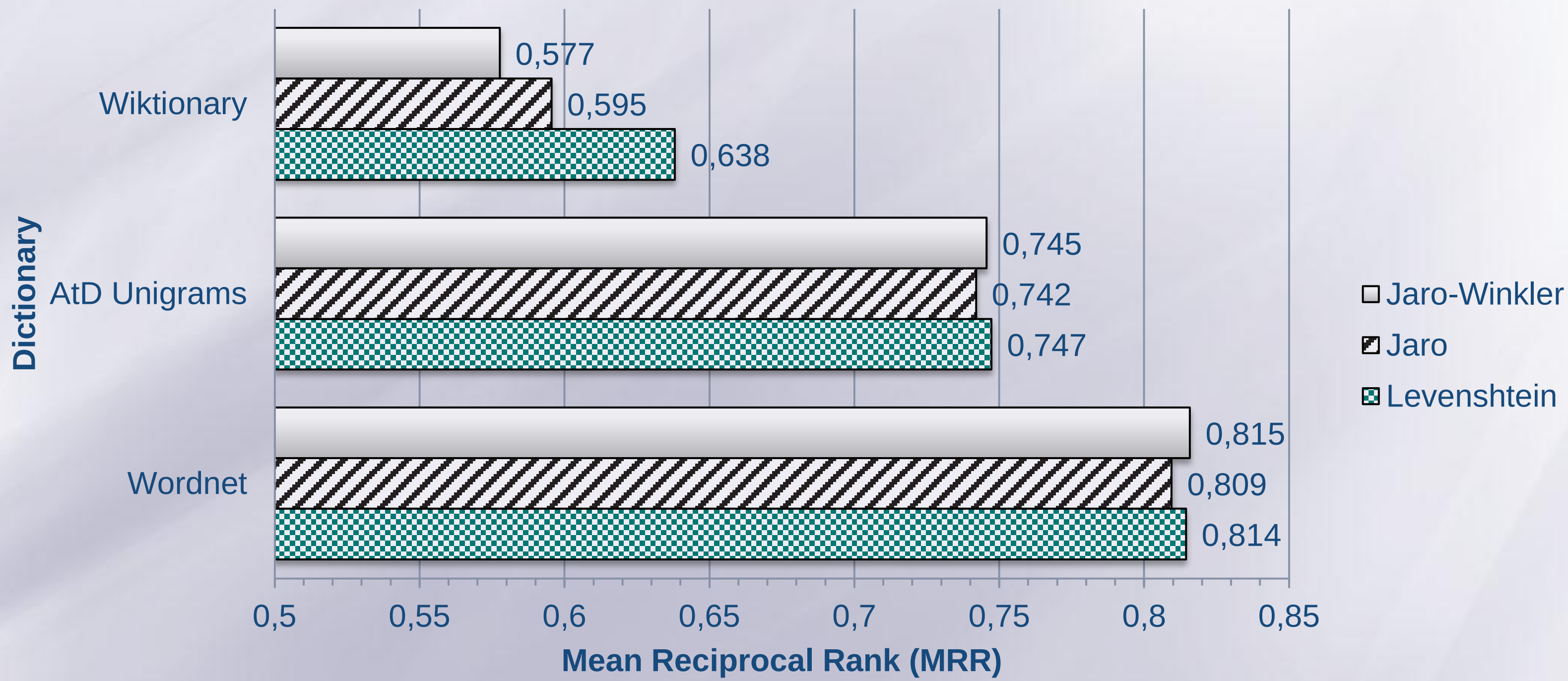
$$EMI_4 = \langle \{WCM, AtD\}, Jaro - Winkler, s, MRR, e \rangle$$

...

$$EMI_9 = \langle \{WCM, Wordnet\}, Levenshtein, s, MRR, e \rangle$$

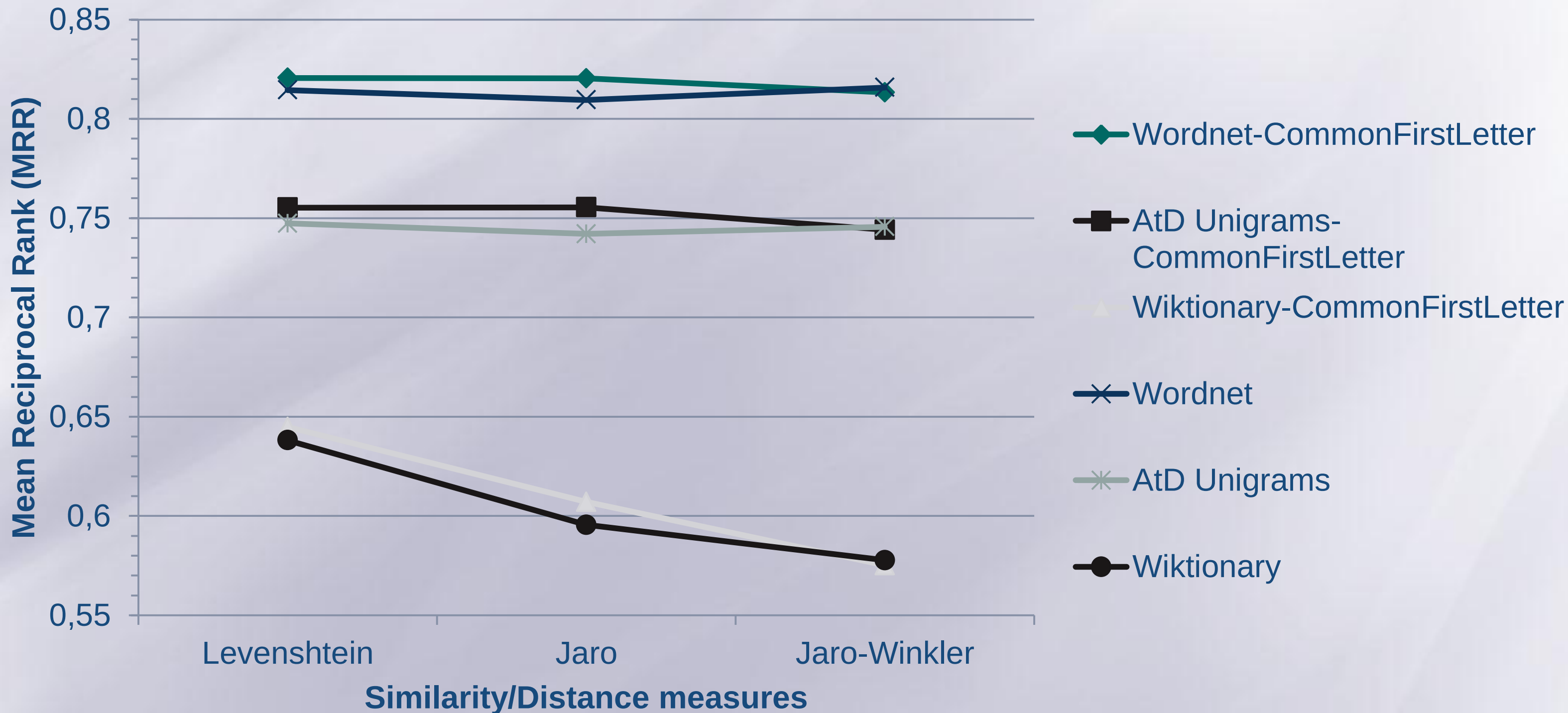
Evaluation (10) : Results

- **MRR of different combinations between similarity/distance measures and dictionaries**



Evaluation (11) : Results

- **Error collection analysis shows that 97% of errors share their first character with their intended target word**
  - → 9 new EMI integrating this heuristic
- **Comparison of MRR values with/without considering the first letter as being common**



Conclusion & further works

Errors correction systems:

→ Identification of difficulties to evaluate approaches

→ Proposal of an evaluation model

→ Implementation of this model in an extensible platform

→ First evaluations of composites error correction systems

Further works:

- Evaluate autonomous error correction systems like Google, Yahoo, Aspell, University of Western Australia prototype, AftertheDeadline (ongoing work)
- Integrate other kinds of similarity measures (like phonetic similarity measures)
  - When considering the Web errors in written content tends to be the same as spoken content [Baron, 2003]
- Evaluations based on other error collections providing additional context [Pedler, 2007]
- Integrate a composite system to an IR system to evaluate indirectly error correction systems over well known IR campaigns like INEX and TREC

Questions

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Contexte : Des erreurs ?... quel intérêt ?

Evolution des processus de production de l'information

- **Qui ?**
  - Professionnels de l'information → Utilisateurs lambda [De Rosnay, 2006]
- **Quoi ?**
  - Contenu textuel proposé par les outils et services fournis sur le Web : pages Web, Blogs, Wiki, …
- **Comment ?**
  - Cadre professionnel → Cadre privé
  - Contrôle de qualité de l'information → libre autopublication (Blogs, Wiki, …)
- **Constat :**
  - **Sources d'information plus nombreuses et plus diversifiées**
  - **Qualité de l'information inégale**
    - *domaine mal connu, vocabulaire non-maitrisé et/ou employé de façon inadaptée, pas de contrôle, pas ou peu de « correction », …*
  - → **+ d'erreurs [Subramaniam, 2009]**

→ **Impact sur les systèmes devant gérer les informations**

→ **En particulier sur la qualité des index produits (et donc sur les performances) :**

- → Accroissement de la taille des index [Ruch, 2002]
- → Silences à l'interrogation

Principaux concepts (1) : Définitions de base

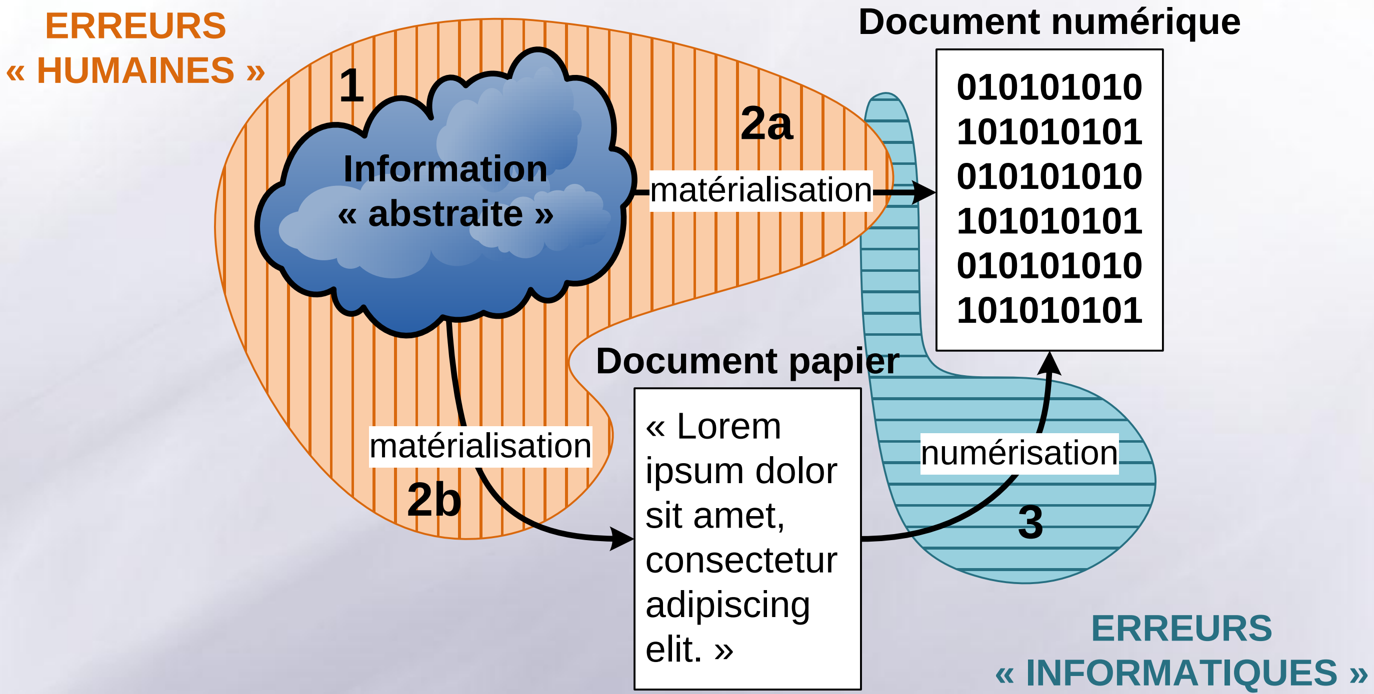
- **Alphabet *A* :**
  - **Ensemble fini des lettres *l* d'une langue.**

- **Mot *m* :**
  - **Séquence ordonnée de k lettres de l'alphabet prise parmi l'ensemble des mots de k lettres A^k.**
    - $\forall l_i \in \mathrm{A}, m \in \mathrm{A}^k \; ssi \; m = l_1, l_2, \ldots, l_{k-1}, l_k$
      - *Exemple : « tree »*
  - **Un mot est appelé mot valide s'il fait partie des mots usités de la langue**

- **Dictionnaire *d* (ou lexique) :**
  - **Ensemble des mots valides d'une langue.**

- **Erreur *e* (ou mot erroné) :**
  - **Mot dont au moins une lettre diffère de la lettre attendue à une position donnée dans la séquence des lettres correspondant à un mot cible correct**
    - $\forall l_i \in \mathrm{A}, \exists l_j \in \mathrm{A} \text{ tel que } \mathrm{i} = \mathrm{j} \text{ et } l_i \neq l_j$
      - *Exemple : « book » → » bok » (non-mot)*
      - *Exemple : « tree » → « three » (mot-réel)*

Origines (1) : Matérialisation de l'information



- **Erreurs humaines à la création (confusion sur le sens, verbalisation de l'idée, association à un mot) de l'information (1) : enfants, étrangers, dyslexiques, …**
- **Erreurs humaines à l'expression (dysorthographie, mauvaise prononciation) et à la saisie :**
  - Informatique : typographie (mauvaise touche, touche défaillante, …) (2a).
  - Manuscrite : dysgraphie (lettres manquantes, lettres mal formées, …) (2b).
- **Erreurs machine à la numérisation (OCR / ASR) de l'information (3).**

➔ Erreurs non mutuellement exclusives → cumul possible

Approches de correction d’erreurs (1)

Approches sémantiques

- **Contraintes :**
  - Contexte obligatoire
  - Utilisation d’une ressource sémantique
- **Intuition [Hirst 1998, Hirst 2005] :**
  - Les mots que le rédacteur a l’intention d’écrire sont généralement sémantiquement liés aux mots présents dans le contexte environnant
  - Erreur de type mot-réel → perte du lien sémantique
  - Application des méthodes de désambiguïsation sémantique à la correction d’erreurs

Approches de correction d’erreurs (2)

Approches statistiques

- **Contrainte :**
  - Apprentissage nécessaire

- **Sans contexte [Mitton, 2009]**
  - **Simple fréquence des mots**
    - *84% des mots corrects sont parmi les mots les plus fréquents [Pedler, 2007]*
    - *62% des erreurs sont parmi les mots les moins fréquents [Pedler, 2007]*

- **Avec contexte**
  - **Statistiques sur la cooccurrence des mots (n-grams)**
    - *Probabilités de trigrammes [Mays, 1991]*
    - *Probabilités de n-grams [Golding, 1999], [Islam, 2009] (entrainés sur le Google Web 1-T n-grams)*
    - *Existence du trigramme dans un corpus de grande taille BNC [Verberne, 2002] → pas de localisation précise de l’erreur*

→ Approches avec contexte donnent de meilleurs résultats

Evaluation (6) : Instanciation/analyse des res.

Mesures de Similarité et de Distance

- **Distance de Levenshtein (distance d'édition classique)**
  - Nombre minimal de caractères qu'il faut effacer, insérer ou substituer pour passer d'un mot à un autre

$$\mathrm{D}_{\mathrm{Levenshtein}}(x_i, y_j) = min\begin{pmatrix} \mathrm{D}(x_{i-1}, y_j) + 1 \\ \mathrm{D}(x_i, y_{j-1}) + 1 \\ \mathrm{D}(x_{i-1}, y_{j-1}) + cout \end{pmatrix}, et\ cout\ vaut\ \begin{cases} 0, si\ x_i = y_j \\ 1, sinon \end{cases}$$

	d	a	i	r	y
d	0	1	2	3	4
i	1	1	1	2	3
a	2	1	2	2	3
r	3	2	2	2	3
y	4	3	3	3	2

$$\mathrm{D}_{\mathrm{Levenshtein}}("dairy", "diary") = 2$$

$$\mathrm{D}_{\mathrm{LevenshteinNorm}}("dairy", "diary") = \frac{2}{\max(5, 5)} = \frac{2}{5} = 0{,}4$$

Evaluation (7) : Instanciation/analyse des res.

Mesures de Similarité et de Distance

- **Autres distances :**
  - **Distance de Jaro**
    - *Basée sur le nombre de caractères correspondants entre deux chaines.*
    - *Deux caractères peuvent être considérés comme correspondants si leurs positions ne sont pas trop éloignées (seuil d'éloignement).*
  - **Distance de Jaro-Winkler**
    - *Idem + les chaines ayant des préfixes similaires sont favorisées.*