

Application of Variable Length N -gram Vectors to Monolingual and Bilingual Information Retrieval

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Introduction

- *blindLight* is a modified vector model with applications to several NLP tasks.
- Goals for this experience:
 - Test the application of *blindLight* to IR (monolingual).
 - Present a simple technique to pseudo-translate query vectors to perform bilingual IR.
- First group participation in CLEF tasks:
 - Monolingual IR (Russian)
 - Bilingual IR (Spanish-English)

Vector Model vs. *blindLight* Model

What's n -gram significance?

- Can we know how important an n gram is within just one document without regards to any external collection?
- Similar problem: Extracting multiword items from text (e.g. **European Union, Mickey Mouse, Cross Language Evaluation Forum**).
- Solution by Ferreira da Silva and Pereira Lopes:
 - Several statistical measures generalized to be applied to arbitrary length **word n -grams**.
 - New measure: **Symmetrical Conditional Probability (SCP)** which outperforms the others.
- So, our proposal to **answer first question**:

If **SCP** shows the most significant multiword items within just one document it **can be applied to rank character n grams for a document according to their significances.**

What's n -gram significance? (cont.)

- Equations for SCP:

$$Avp = \frac{1}{n-1} \sum_{i=1}^{i=n-1} p(w_1 \dots w_i) \cdot p(w_{i+1} \dots w_n)$$

$$SCP_f((w_1 \dots w_n)) = \frac{p(w_1 \dots w_n)^2}{Avp}$$

- $(w_1 \dots w_n)$ is an n -gram. Let's suppose we use quad-grams and let's take **(igni)** from the text **What's n-gram significance**.
 - $(w_1 \dots w_1) / (w_2 \dots w_4) = (\mathbf{i}) / (\mathbf{gni})$ ①
 - $(w_1 \dots w_2) / (w_3 \dots w_4) = (\mathbf{ig}) / (\mathbf{ni})$
 - $(w_1 \dots w_3) / (w_4 \dots w_4) = (\mathbf{ign}) / (\mathbf{i})$ ②
 - For instance, in ① $p((w_1 \dots w_1)) = p((\mathbf{i}))$ would be computed from the relative frequency of appearance within the document of n -grams starting with **i** (e.g. **(igni)**, **(ific)**, or **(ican)**).
 - In ② $p((w_4 \dots w_4)) = p((\mathbf{i}))$ would be computed from the relative frequency of appearance within the document of n -grams ending with **i** (e.g. **(m_si)**, **(igni)**, or **(nifi)**).

What's n -gram significance? (cont.)

- Current implementation of *blindLight* uses quad-grams because...
 - They provide better results than tri-grams.
 - Their significances are computed faster than $n \geq 5$ n -grams.
- ¿How would it work mixing different length n -grams within the same document vector? Interesting question to solve in the future...
- Two example *blindLight* document vectors:
 - Q document: Cuando despertó, el dinosaurio todavía estaba allí.
 - T document: Quando acordou, o dinossauro ainda estava lá.
 - Q vector (45 elements):
{(Cuan, 2.49), (l_di, 2.39), (stab, 2.39), ..., (saur, 2.31), (desp, 2.31), ..., (ando, 2.01), (avía, 1.95), (_all, 1.92)}
 - T vector (39 elements):
{(va_1, 2.55), (rdou, 2.32), (stav, 2.32), ..., (saur, 2.24), (noss, 2.18), ..., (auro, 1.91), (ando, 1.88), (do_a, 1.77)}
- ¿How can such vectors be numerically compared?

Comparing *blindLight* doc vectors

- Comparing different length vectors is similar to pairwise alignment (e.g. Levenshtein distance).
- **Levenshtein distance:** number of insertions / deletions / substitutions to change one string into another one.
- Some examples:
 - **Bioinformatics:** AAGTGCCTATCA vs. GATACCAAATCATGA (distance: 8)
 - AAG--TGCCTA-TCA---
 - ---GATACCAAATCATGA
 - **Natural language:** Q document vs. T document (distance: 23)
 - Cuando_desper-tó,_el_dino-saurio_todavía_estaba_allí.
 - Quando_--acordou,_-o_dinossaur-o_--ainda_estava_--lá.
- **Relevant differences between text strings and *blindLight* doc vectors make sequence alignment algorithms not suitable:**
 - Doc vectors have term weights, strings don't.
 - Order of characters (“terms”) within strings is important but unimportant for *bL* doc vectors.
- **Anyway... Sequence alignment has been inspiring...**

Comparing *blindLight* doc vectors (cont.)

- Some equations:

Comparing *blindLight* doc vectors (cont.)

$$\mathbf{Pi} = S_{Q\Omega T} / S_Q = 20.48 / 97.52 = 0.21$$

$$\mathbf{Rho} = S_{Q\Omega T} / S_T = 20.48 / 81.92 = 0.25$$

Information Retrieval using *blindLight*

- Π (Pi) and P (Rho) can be linearly combined into different association measures to perform IR.
- Just two tested up to now: Π and $\frac{\Pi + \text{norm}(\Pi P)}{2}$ (which performs slightly better).
- IR with *blindLight* is pretty easy:
 1. For **each document** within the **datas** and stored.
 2. When a **query** is submitted to the system:
 - a) A **4-gram (Q)** is computed for the query.
 - b) For **each doc vector (T)**:
 - i. Q and T are Ω -intersected obtaining Π and P .
 - ii. Π and P are combined into a unique value Rho , and thus $Pi \cdot Rho$, values are negligible when compared to Pi . norm function scales $Pi \cdot Rho$ values into the range of Pi values.
 - c) A **reverse ordered list of documents** is built and returned to **answer** the query.
- **Features and issues:**
 - No indexing phase. Documents can be added at any moment. 😊
 - Comparing each query with every document not really feasible with big data sets. ☹️

Bilingual IR with *blindLight*

We have compared n -gram vectors for pseudo-translations with vectors for actual translations (Source: Spanish, Target: English).

38.59% of the n -grams within pseudo-translated vectors are also within actual translations vectors.

28.31% of the n -grams within actual translations vectors are present at pseudo-translated ones.

Promising technique but thorough work is required.

Bank	2.92
Worl	2.70
ld_B	2.70
...	
Hali	2.51
ifax	2.51
...	
cumb	2.33
mbre	2.33
...	
ssio	2.24
ussj	2.23
ards	2.21
ax_e	2.21
...	
_IMF	2.19
...	
FMI_	2.03
bre	2.03
n_Ha	2.03
...	
G7	1.90
by	1.89
the_	1.86
...	
t_th	1.61
n_th	1.42

Results and Conclusions

- **Monolingual IR within Russian documents:**
 - 72 documents found from 123 relevant ones.
 - Average precision: 0.14
- **Bilingual IR using Spanish to query English docs:**
 - 145 documents found from 375 relevant ones.
 - Average precision: 0.06.
- **Results at CLEF are far, far away from good but anyway encouraging... Why?!**
 - Quick and dirty prototype. *“Just to see if it works...”*
 - First participation in CLEF.
 - Not all topics achieve bad results. **THE PROBLEM** are mainly **broad topics** (e.g. **Sportswomen and doping, Seal-hunting, New Political Parties**).
 - Similarity measures are not yet tuned. Could genetic programming be helpful? Maybe...
- **To sum up, *blindLight*...**
 - ...is an extremely simple technique.
 - ...can be used to perform information retrieval (among other NLP tasks).
 - ...allows us to provide bilingual information retrieval trivially by performing “pseudo-translation” of queries.

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Danke schön

ありがとう

Ευχαριστώ

Dank u

Thank you

Obrigado

Kiitos

Спасибо

Merci

Tack

Grazie

谢谢

Gracias