## Intrinsic Dimensionality in IR

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Paper:

Vincent Claveau, Indiscriminateness in representation spaces of terms and documents, ECIR 2018

## Local Intrinsic Dimensionality

- to portray the neighboring documents of a query within distance
- how many variables are needed to generate a good approximation of the query
- as an interpretation of indiscriminateness of dataset

## Local Intrinsic Dimensionality in IR

\* Assume that there are two balls with center  $c_1$  and  $c_2$  and radius of  $\varepsilon_1$  and  $\varepsilon_2$ :

The ratio between the volumes of these balls can be expressed as:

$$\frac{volume(B(x,\epsilon_1))}{volume(B(x,\epsilon_2))} = \left(\frac{\epsilon_1}{\epsilon_2}\right)^m$$

$$m = \frac{\ln(volume(B(x, \epsilon_1))) - \ln(volume(B(x, \epsilon_2)))}{\ln \epsilon_1 - \ln \epsilon_2}$$

# Local Intrinsic Dimensionality in IR

 Replace the volume itself with the number of points

$$\hat{m} = \frac{\ln |(B(x, \epsilon_1)| - \ln |B(x, \epsilon_2)|}{\ln \epsilon_1 - \ln \epsilon_2}$$

RSV(Retrieval Status Value)

$$RSV(q,d) = \sum_{t \in q} w_q(t) \cdot w_d(t)$$

#### Distribution of the Documents

⇒ Documents fall in the space with two thresholds values ε1 and ε2 (ε1 ≥ ε2).

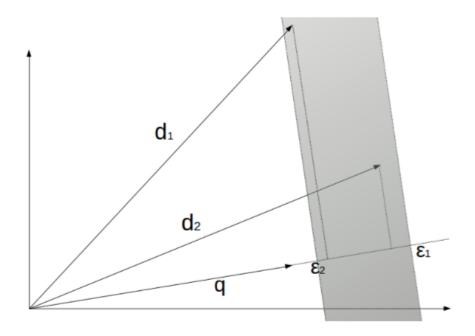


Fig. 3: In gray: portion of space defined by the set of points whose scalar products with a normed vector q lie between  $\epsilon_1$  and  $\epsilon_2$ 

#### Distribution of the Documents

The close documents may have any distance because of no normalization.

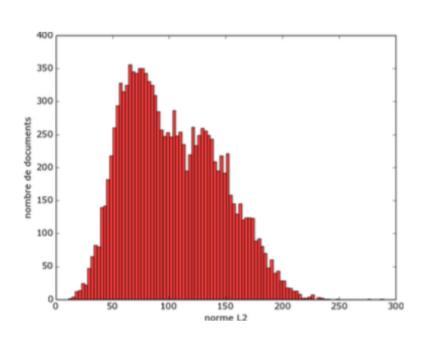


Fig. 1: Distribution of the L2 norms of documents in Tipster collection under BM25+ (modified version of BM25 proposed by [16])

#### Estimate with Power Law

- By repartitioning the distance between q and documents, we can estimate the intrinsic dimension.
- \* The distribution of documents follow the Power Law, so we can interpret intrinsic dimension  $\alpha$  as the exponent, which is characteristic of indiscriminateness of the data.
  - x represents the RSV score

$$f(x) = \lambda x^{-\alpha}$$
 with  $\lambda$  a constant and  $\alpha > 1$ 

#### Estimate with Power Law

\* Due to the feature of indiscriminateness, we can estimate  $\alpha$  with the neighbors of query and set a threshold to acquire  $\alpha$  with the top n RSV scores.

$$\hat{\alpha} = 1 + n \cdot \left(\sum_{i=1}^{n} \ln \frac{x_i}{x_{min}}\right)^{-1}$$

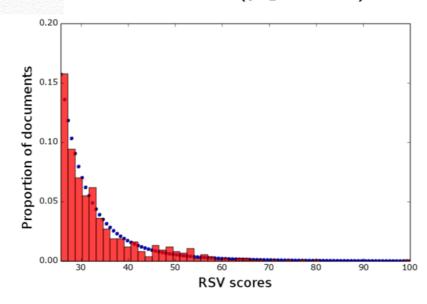


Fig. 4: Example RSV values repartition (red histogram) and the corresponding Power Law (blue) obtained with log-likelihood estimate of  $\alpha$  from the RSV values

### Experiment in IR

- \* The distribution of documents determines the retrieval precision, so we can assess the difficulty of query by exploring the correlation between the  $\alpha$  and the AP(Average Precision).
- Low retrieval happens with high indiscriminateness around query.

coefficient	I	p-value
Pearson $r$	-0.7150	$5.43e^{-09}$
Pearson $r$ Spearman $\rho$	-0.7753	$3.82e^{-11}$
Kendall $ au$	-0.5755	$3.69e^{-09}$

Table 2: Correlations (and their associated p-values) between AP and index  $\alpha$  on Tipster with a BM25+ model

coefficient		
Pearson $r$	-0.4919	$9.85e^{-08}$
Spearman $\rho$	-0.6141	$3.26e^{-12}$
Pearson $r$ Spearman $\rho$ Kendall $\tau$	-0.4494	$1.14e^{-11}$

Table 3: Correlations (and their associated p-values) between AP and index  $\alpha$  on OHSUMED with a Dirichlet LM ( $\mu = 1000$ )

## Experiment in Query Expansion

- Adding the closest semantic term to the original query
- We can estimate the α to obtain the properties of the word space, then use it to filter the expansions.
- The author set two experiments with different filters for the expansion.

## Experiment in Query Expansion

#### Two filters:

- Filter 1
  - \* compute the  $\alpha$  for each word of the query and pick out the neighboring words of the word with  $\alpha$  lower than the threshold (average  $\alpha$  of the query in this case)
- ⇒ Filter 2
  - $\Leftrightarrow$  filter the word by filter 1 first, then choose the neighbors of words with  $\alpha$  below a certain value for a second time

## Experiment in Query Expansion

With close examination, words with high
 α are polysemic or common, such as use, way, young, etc.

	MAP	$\operatorname{R-Prec}$	P@5	P@10	P@50	P@100
No expansion	21.78	30.93	92.80	89.40	79.60	70.48
with expansion	+13.80	+9.58	+2.16	+4.03	+5.58	+8.26
with expansion $+$ Filter 1	+16.22	+10.78	+3.02	+4.47	+9.20	+12.51
with expansion + Filter 1 & 2	+22.83	+13.00	+2.56	+6.31	+14.10	+21.39

Table 4: Relative performance gain (%) on Tipster with query expansion with and without filtering; spectral lexicon

	MAP	$\operatorname{R-Prec}$	P@5	P@10	P@50	P@100
No expansion	21.78	30.93	92.80	89.40	79.60	70.48
with expansion	+13.52	+9.50	+2.59	+3.36	+8.29	+9.99
with expansion $+$ Filter 1	+15.73	+9.27	+2.22	+4.96	+9.63	+14.41
with expansion $+$ Filter 2	+20.76	+13.63	+3.88	+5.82	+10.15	+14.27

Table 5: Relative performance gain (%) on Tipster with query expansion with and without filtering; Word2Vec

### Conclusion

- \* Leveraging the notion of intrinsic dimensionality in place of the distance to evaluate the similarity in IR raises question.
- Practically, this technique can help form a better query for online search by suggesting more precise words when a word is typed in and its α is rather high.

Thank you for your attention