

INAOE's participation at ImageCLEF 2016: Text Illustration task

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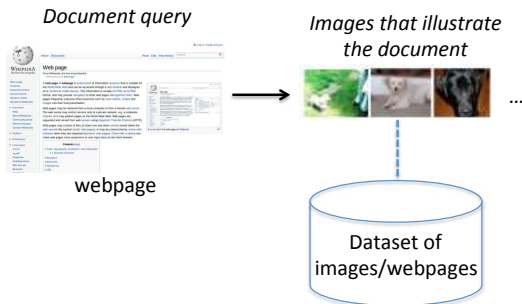


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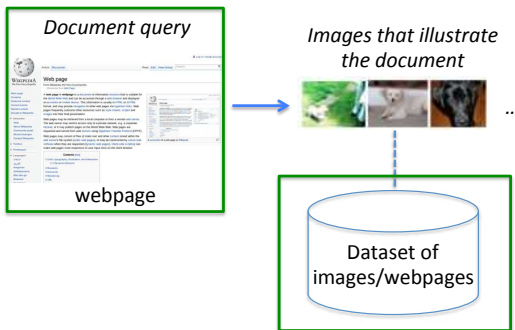
TI at ImageCLEF

- A set of images embedded in webpages are available to illustrate document queries.



TI as IR-based approach

1. **Representing documents.**
2. **Retrieval stage.**



The hypothesis is that relevant images can be derived from related webpages.

Representing documents

We use two popular representations:

1. Bag-of-words (BoW) representation defines each document as histograms of word occurrences.
2. Word2vec representation incorporates distributional semantics to text documents with learned word vectors.



Representing documents

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Retrieval stage

A document query q_j under a specific representation is used to retrieve a set of relevant items $\{(d_h, l_h) : (d_h, l_h) \in \mathcal{D}\}$.

$$\text{similarity}(q_j, d_i) = \text{cosine}(\mathbf{q}_j, \mathbf{d}_i) = \frac{\mathbf{q}_j * \mathbf{d}_i}{\|\mathbf{q}_j\| \|\mathbf{d}_i\|} \quad (1)$$

where $\mathbf{q}_j, \mathbf{d}_i$ are the representations of the document query q_j , and the i^{th} document d_i from the collection \mathcal{D} , respectively.

Some details about document representation

1. BoW representation:

- ▶ It was built filtering terms with high frequency.
- ▶ Using TF-IDF (term frequency inverse document frequency) weighting scheme.
- ▶ Dimension of the extracted vocabulary is about 15,000.

2. Word2vec representation:

- ▶ Each document is represented by the average word vectors (Le & Mikolov, 2014).
- ▶ Using learned word vectors from Wikipedia (Mikolov et al., 2013).
- ▶ Dimension of the vectors: 300 values.

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Quantitative results

Cuadro: Recall@K for full 180K test set.

Team	RUN	Recall (%)						
		R@1	R@5	R@10	R@25	R@50	R@75	R@100
<i>Baseline</i>	chance	0.00	0.00	0.01	0.01	0.03	0.04	0.05
CEA	cbs.flickrgroup.FS.valid	0.02	0.10	0.22	0.48	0.84	1.16	1.44
	cbs.wordnet.FS.valid	0.03	0.12	0.23	0.53	0.97	1.38	1.74
	cbs.mergeA.valid	0.14	0.56	0.97	1.90	2.98	3.82	4.47
	cbs.mergeB.valid	0.18	0.63	1.05	1.97	3.00	3.87	4.51
	cbs.mergeC.valid	0.18	0.62	1.04	1.95	2.99	3.85	4.50
	wam5.kcca1.idsQueries.all.valid	0.11	0.36	0.62	1.11	1.68	2.11	2.47
	warm7.idsQueries.10BWS.all.valid	0.18	0.63	1.07	1.93	2.93	3.69	4.33
INAOE	run1.bow+tfidf.thr5p	28.75	63.50	75.48	84.39	86.79	87.36	87.59
	run2.d2v.thr5p	2.57	5.65	7.71	11.76	16.69	20.34	23.40
	run3.d2v+tfidf.thr5p	3.68	7.73	10.46	15.62	21.36	25.48	28.78

Qualitative results: short texts



Figura: Given the text document (top), the top of retrieved images. First row, output images from BoW. Second row, output images from word2vec.

Qualitative results: long texts

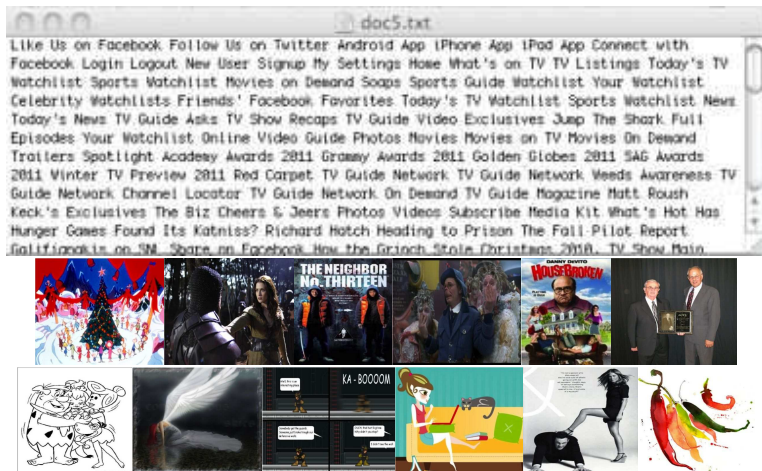


Figura: Given the text document (top), the top of retrieved images (first row, output images from BoW. Second row, output images from word2vec.



Conclusions

- ▶ According to the performed evaluation we conclude that, relevant images can be derived from related webpages, so it is possible to use IR techniques.
- ▶ BoW representation obtained outstanding performance and was more robust to deal with long documents.
- ▶ Finally, the performed experiments under different representations give an initial point of comparison for future approaches.
- ▶ As future work, we plan to incorporate mix information (textual-visual).

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Gilbert A., Piras L., Wang J., Yan F., Ramisa A., Dellandrea E., Gaizauskas R., Villegas M., Mikolajczyk K. (2016)

Overview of the ImageCLEF 2016 Scalable Concept Image Annotation Task.
In: *CLEF2016 Working Notes*, CEUR Workshop Proceedings, Évora, Portugal.



Mikolov T., Chen K., Corrado G., Dean J. (2013)

Efficient estimation of word representations in vector space.
In: *CoRR*, abs/1301.3781.



Jones K.S. (1972)

A statistical interpretation of term specificity and its application in retrieval.
In: *Journal of Documentation* 28, 11-21.



Le Q.V., and Mikolov T. (2014)

Distributed representations of sentences and documents.
In: *CoRR*, abs/1405.4053.



Hodosh M., Young P., Hockenmaier J. (2013)

Framing image description as a ranking task: Data, models and evaluation metrics.
In: *Journal Artif. Int. Res.* 47, 853-899.



Pellegrin, L., Vanegas, J.A., Arevalo, J., Beltrán, V., Escalante, H.J., Montes-Y- Gómez, M., González, F. (2015)

INAOE-UNAL at ImageCLEF 2015: Scalable Concept Image Annotation.
In: *CLEF2015 Working Notes*, CEUR Workshop Proceedings, Toulouse, France.

Thank you for your attention, questions?



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