A Supervised Term-Weighting Method and its Application

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Motivations for Term Weighting

- Improve Information Retrieval Systems
- Text Representation for Classification

Term Importance is typically taken as a fixed value independent of the task at hand.

Motivations for Context-based Term Weighting

- Query formulation
- Term Relevance Scoring
- Variable Selection

Previous Work

Salton and Buckley (1988) claimed that at least **three main factors** are required in any term weighting scheme.

- **Local factor:** frequent terms are semantically close to the content of the document.
  - helps to improve recall.
- **Global Factor:** associated with each term, represents how frequent the term is in the document collection.
  - helps to improve precision.
- **Normalization Factor:** to penalize large documents.

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$$\mathbf{v}_{normalized} = \frac{1}{\sqrt{\sum_{i=1}^{n} v_i^2}} \times \mathbf{v}$$

Proposed Technique

DESCR

The **descriptive relevance** of a term in a class stands for a simple idea: those terms that occur in many documents of a given class are good descriptors of that class.

DISCR

The **discriminative relevance** of a term in a class is based on the idea that a term is a good discriminator of a class if it tends to occur only in documents of that class.

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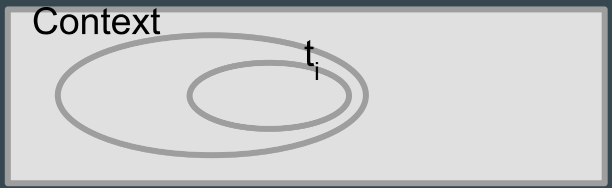

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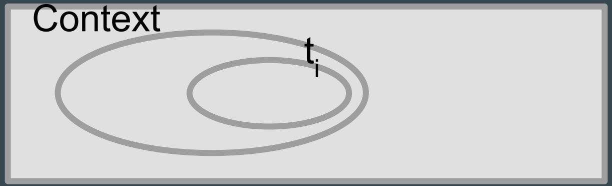

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FDD

$$\mathrm{FDD}_\beta(t_i, c_k) = (1+\beta^2)\frac{\mathrm{DISCR}(t_i, c_k) \times \mathrm{DESCR}(t_i, c_k)}{(\beta^2 \times \mathrm{DISCR}(t_i, c_k)) + \mathrm{DESCR}(t_i, c_k)}.$$

Data Collection

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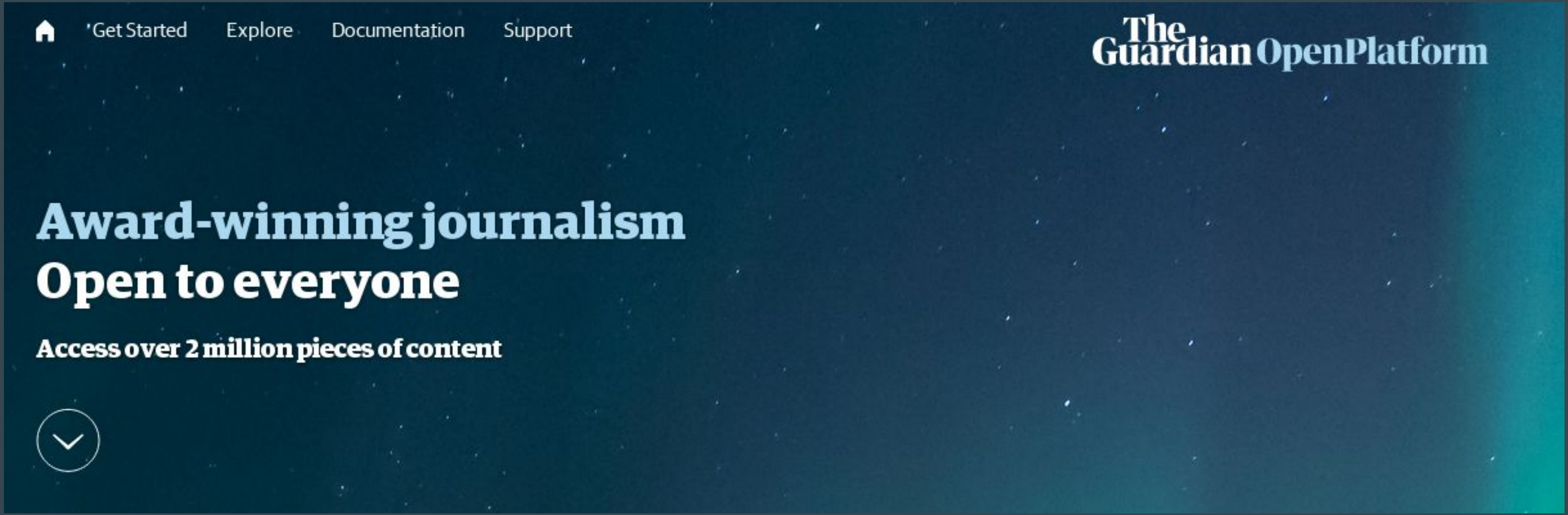

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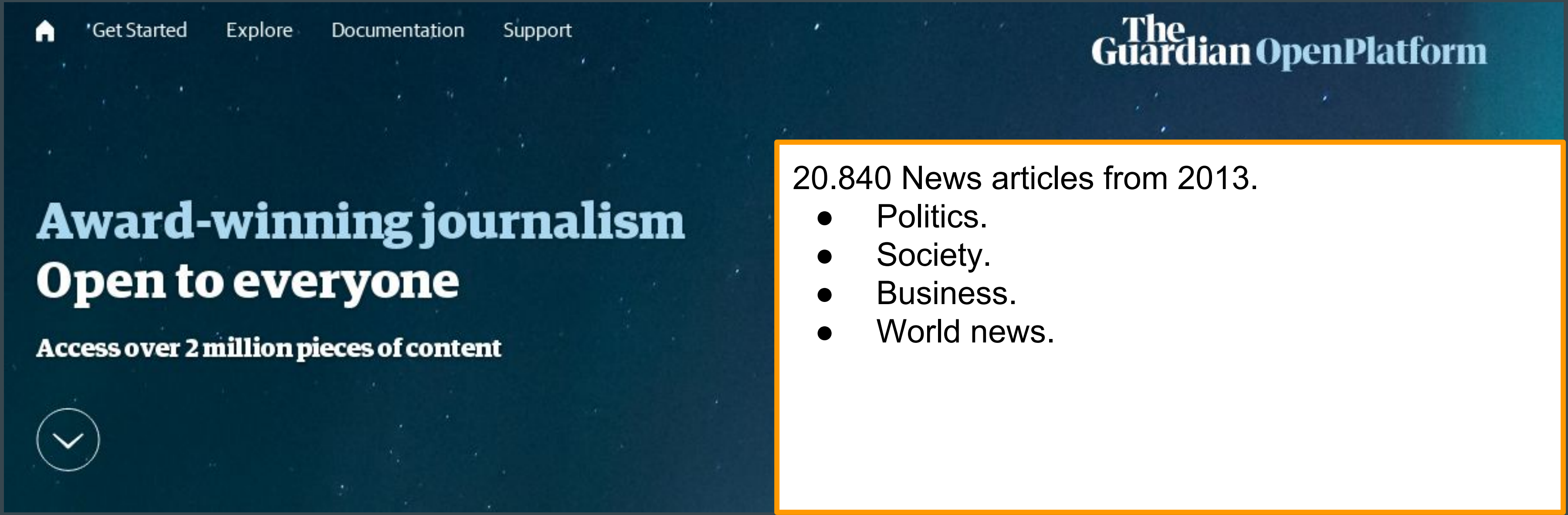

20.840 News articles from 2013.

- Politics.
- Society.
- Business.
- World news.

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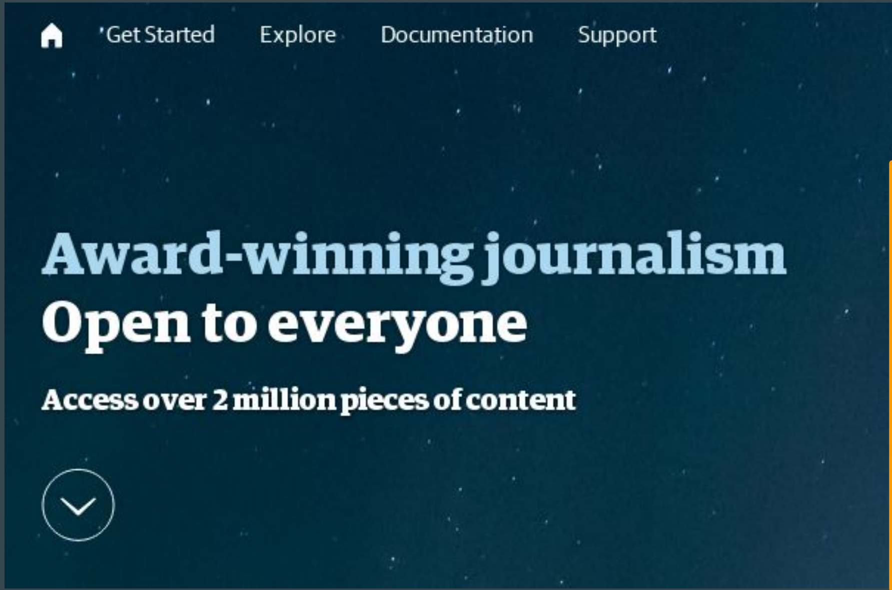

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1.689 News articles from January 2013 were manually labelled by experts.

Validation I

- **Validation by User Study**
  Terms were strategically selected from the dataset and manually scored by the users with a score between 0 and 5. We want to see the correlation between the human subject and our technique.
  - A set of 50 terms for parameter tuning
  - A set of 100 terms for validation

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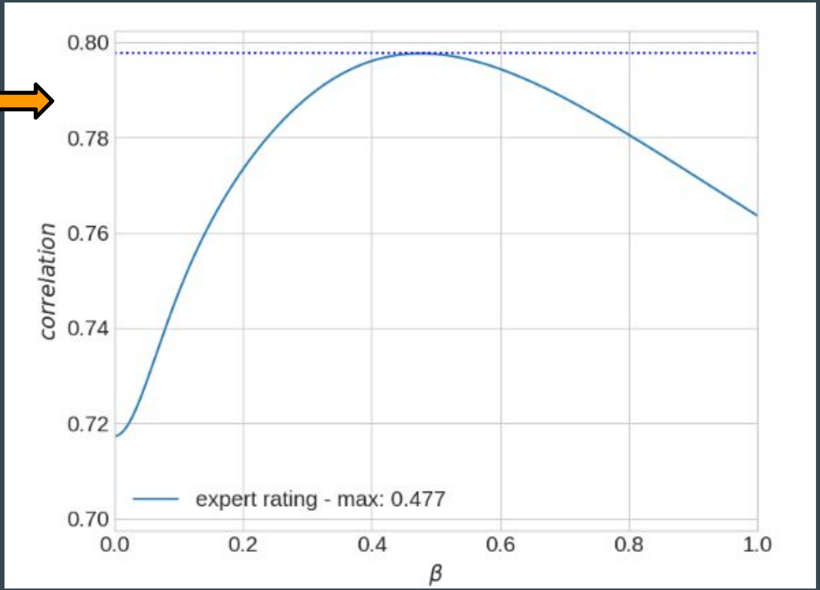

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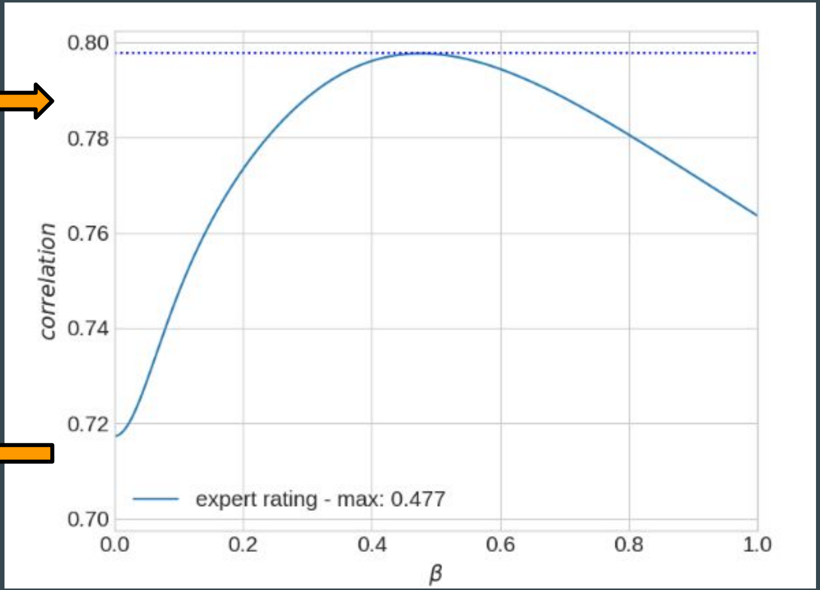

non-experts and experts	non-experts and FDD$_{0.477}$	experts and FDD$_{0.477}$
$\mu = 0.80383$, $\sigma = 0.053205$	$\mu = 0.685598$, $\sigma = 0.054969$	$\mu = 0.752352$, $\sigma = 0.018904$

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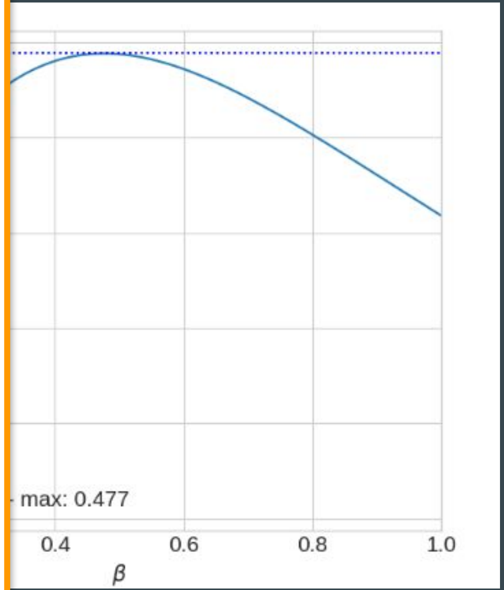
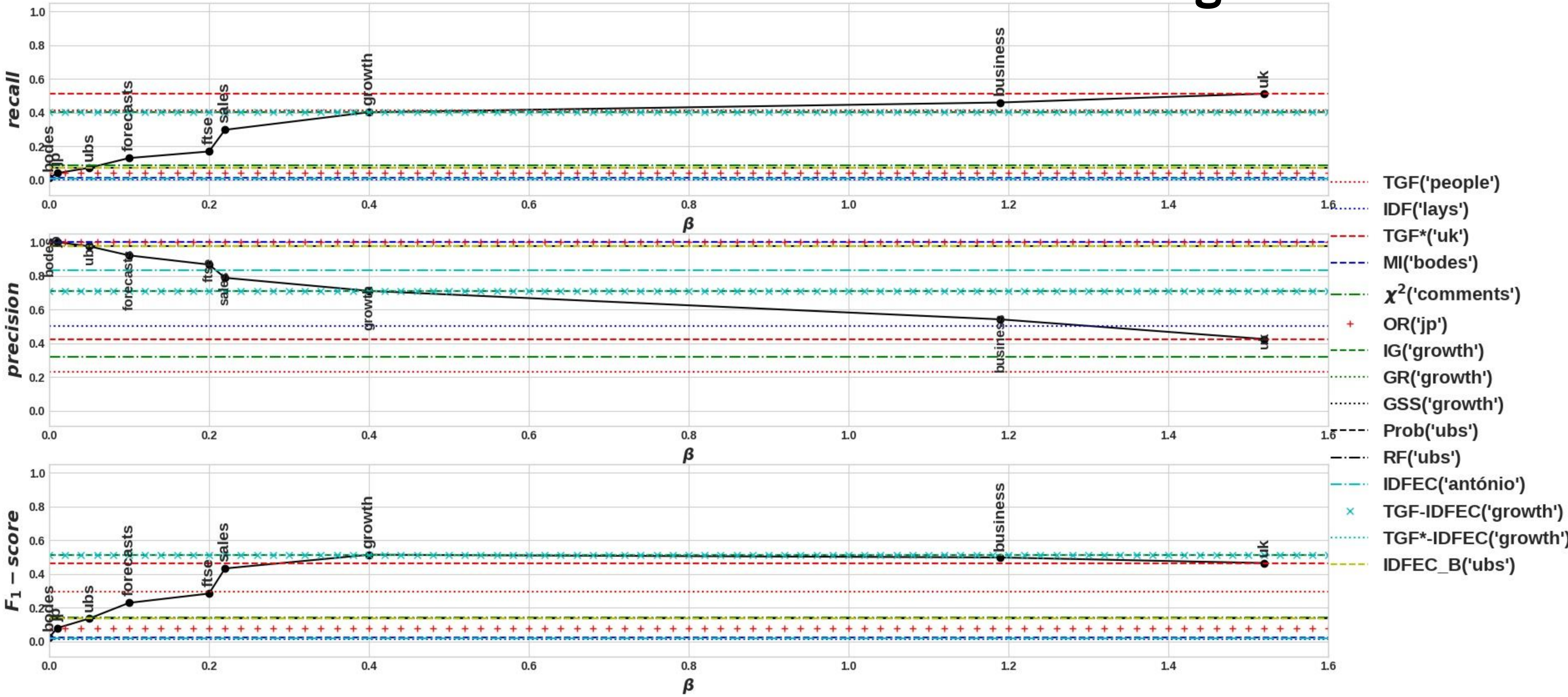
Method	non-expert (averaged)	expert (averaged)	non-expert and expert (averaged)
TGF	0.283553	0.365037	0.332324
IDF	-0.488816	-0.563704	-0.539138
TGF*	0.574110	0.642607	0.623198
MI	0.697053	0.659659	0.694604
χ^2	-0.164537	-0.087771	-0.128992
OR	0.432627	0.306599	0.378188
IG	0.663296	0.705736	0.701123
GR	0.663296	0.705736	0.701123
GSS	0.722761	0.757015	0.757807
Prob	0.654187	0.697007	0.691990
RF	0.472824	0.407394	0.450543
IDFEC	-0.226397	-0.325872	-0.283050
TGF-IDFEC	0.603975	0.676551	0.655882
TGF*-IDFEC	0.721871	0.774026	0.766110
IDFEC_B	-0.221061	-0.320304	-0.277466
DESCR	0.574110	0.642607	0.623198
DISCR	0.662481	0.610804	0.651848
FDD$_{0.477}$	**0.735456**	**0.791969**	**0.782264**



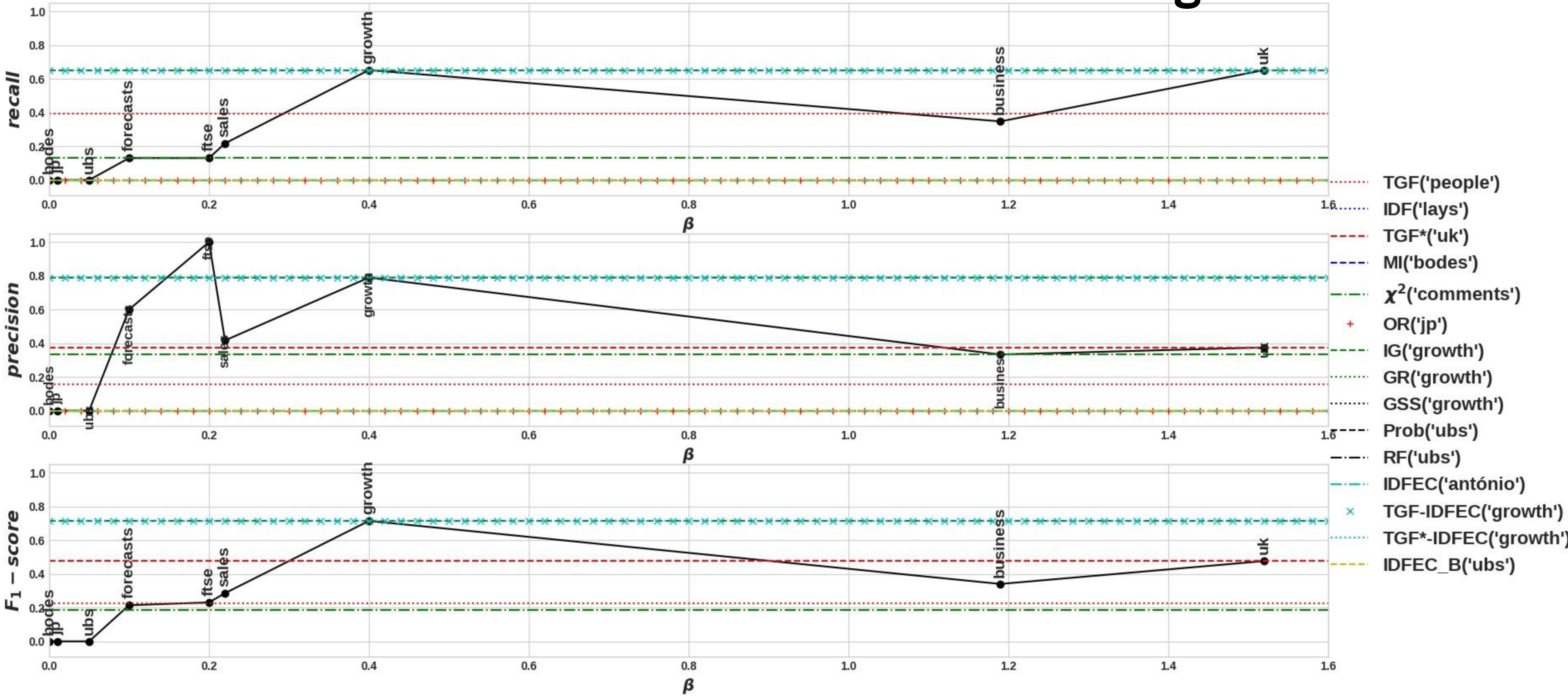
Validation II - Retrieval Effectiveness

- A reduced set consisting of 100 expert-labeled news articles (not included in the training set) was used as the validation set.
- The top-rated terms according to each technique were used as queries. The precision, recall, and f1-measure was reported.

Validation II - Retrieval Effectiveness On Training



Validation II - Retrieval Effectiveness On Testing



Conclusion and Future Work

- Good performance as an estimator of human subjects' relevance judgments.
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- Good performance as a mechanism for selecting good query terms.
- Test FDD with more than two categories.
- Test differents β for differents datasets.
- A subsequent modeling step would be to identify different types of dependency relations between these variables (such as causal relations and close association).

Conclusion and Future Work

- Good p… …ments.
- Good p…
- Test FD…
- Test dif…
- A subse… …dependency relation… …ssociation).

THANK YOU
Questions?
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