Trust me, I am an Expert: Predicting the Credibility of Experts for Statements

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Abstract

Nowadays, information on any topic can be researched on the Internet. However, in addition to reputable news sources, there is also a great deal of fake news that is disseminated, e.g., via social media or in established newspapers. Thus, the veracity must be assessed for each piece of information. People, parties, and organizations want to push through their interests and sometimes do not hesitate to spread fake news. For some time now, one popular means has been to quote (supposed) experts in a field. For example, —due to his authority— Albert Einstein is often quoted by believers in God although he was primarily concerned with physics while his quotes on God are taken out of context.

In this paper, we define a new task of expert suitability prediction and evaluate methods to assess the credibility of a person with reference to a statement and its context and compare it to state-of-the-art approaches applying transformer-based embeddings. In an R4 cycle in CBR this approach could be used for the ranking. In this pilot study, we restrict our experiments to researchers, which allows us to derive their expertise from their publications. Furthermore, we make a manually labeled dataset consisting of 1,700 (statement,expert) pairs where suitable experts were tediously searched out together with valuable context information (such as convincing text parts of the experts' contexts towards a statement) publicly available to stimulate further research in this very important, but up to now underrepresented area of fake news detection.

Keywords

Fake News, Expert Validation, Claim Validation, Argumentation

1. Introduction

The Internet offers countless opportunities to consume information, and social media such as Facebook and Twitter increase the likelihood of contact with news [1]. However, the consumption of news is not always consciously selected, but users come across suggested articles because they have been shared by their contacts, for example. Random access to news causes the number of report sources to increase. At the same time, the potential for encountering misinformation or disinformation increases as well. Misinformation describes unintentionally misinterpreted information which is thus spread due to a lack of knowledge. In contrast, disinformation consists of news reports created with the intention of spreading false information. This makes

it particularly important to recognize fake news, which includes both misinformation and disinformation, and thus distinguish it from true facts. Misleading information has far-reaching consequences and the global economic damage is estimated at 78 billion US dollars annually [2]. This affects politics and industries as the finance and the advertising sector. Especially with complex topics such as corona viruses, it is difficult to distinguish a serious report from false news not only for laymen.

Due to its effectiveness, a frequently used tactic to strengthen the message of own views is to quote scientists on topics that are not the core area of their research. An infamous example is Albert Einstein, who is often quoted by believers in God, although Einstein was primarily concerned with physics and his quotes on God are taken out of context [3]. In other words, people misuse the authority of an expert in order to increase the trustworthiness of another matter, while the expert's expertise is rather to be found somewhere else. Regarding this problem, it is not even important whether the experts are aware that they have been used for a statement of another field, or whether they do this themselves. Accordingly, due to the ever increasing and faster dissemination of information it is important to have a system that checks whether the person making a statement or being cited for a statement also has the expertise with regard to the topic of the statement to believe it and not only a lot of authority.

To tackle this issue, this paper presents a pilot study for validating the suitability of experts towards statements. To the best of our knowledge, there is no prior work addressing this. Since it is harsh and controversial in practice to generalize when a person is an expert in a field, we restrict our experiments to researchers only, since (1) we can derive their expertise from their publications and (2) the expertise of scientists with experience in a field is usually not disputed; the extension of the application to non-scientists is then part of the future work. Certainly, people who neither conduct research on a topic nor have published on it can also be experts on a number of subjects but they are usually not consulted as experts on controversial matters to increase trust such as energy supply or behavior in the event of military action. Thus, in this paper we pursue to answer the question whether somebody would believe a supposed expert if they made a certain statement. However, to find out whether the expert in question actually made the statement is not part of this work. In CBR, this approach could be used as ranking component in the R4 cycle.

We make the following contributions:

(i) We define the new task of assessing researchers' expertise regarding controversial statements.

(ii) We provide a dataset containing 1,700 manually labeled (statement,expert) pairs along with important contextual information to push this research forward.[1]

(iii) We investigate the performance with state-of-the-art machine-learning approaches to make predictions about researchers' expertise towards statements.

Next, we address related work in Section 2. In Section 3 we define the task of assessing researchers' expertise regarding controversial statements and introduce the dataset. Then, we present our methods and report the results of our evaluation in Section 4. We conclude the paper and give an outlook to future work in Section 6.

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[1]The dataset is available at the following link: https://doi.org/10.5281/zenodo.6586678

2. Related Work

Due to the increasing prevalence of fake news, the research area of fact checking is becoming more and more prominent in NLP. However, to the best of our knowledge, no one has validated expert statements and particularly not by examining scientific publications of researchers. Hence, we briefly survey the state-of-the-art in (1) research in general, (2) evidence-based research studies, as our approach might be used to identify resources to fact check claims, (3) credibility prediction studies, and (4) data fusion and worker expertise in crowdsourcing, as our method has some similarities to them.

Fake News detection in general   In their meta-analysis, Thorne et al. [4] summarize the current state of research of automatic fact-checking and divide claim validation into verification and fact-checking. Basically, there are two concepts of how the facts of claims are verified. While some approaches perform verification using knowledge bases [5], e.g. by using WordNet [6], others use Natural Language Inference [7] to check short sentences. The tool ClaimBuster [8] determines how check worthy each sentence of a given input is and finds similar statements in a database to assess its truthfulness. While some works rely solely on the sentence [9], others consider additional metadata such as speaker profiles [10, 11] or linguistic features [12, 13, 14, 15, 16]. Other works address the trustworthiness of websites by evaluating the graph connections and ignore the content [17].

Evidence-Based Research Studies and Credibility Prediction Studies   Fields that are related to our paper to a certain degree are, to the best of our knowledge, evidence-based research studies and credibility prediction studies.

Those works consider social networks such as Twitter and measure, e.g., user influence [18]. The work by Canini et al. [19] is closest to ours, as it ranks social network users according to their credibility on a topic by combining the analysis of the link structure of social networks with topic models of the content of messages to identify and evaluate topically relevant and credible sources of information in social networks. They define credibility as the combination of expertise and trust, and expertise as the support of other professionals [20]. Note that in our paper, this support of researchers is achieved through the acceptance of papers in a peer-reviewed process at a conference.

Source Credibility in Data Fusion and Worker Expertise in Crowdsourcing   Other related fields are source credibility in data fusion and worker expertise in crowdsourcing. In the field of data fusion, the goal is to combine data from multiple sources to achieve a more accurate overall picture than if only one data source is considered. For the calculation of the overall picture, it is important to know the credibility of the individual sources and to include them in the calculation [21]. MacDonald et al. [22] modeled expert ranking as a voting problem. In the ranking, the documents voted for the expert candidates and the score of each candidate was calculated using various data fusion techniques, e.g. Reciprocal Rank. Also in crowdsourcing systems such as Amazon Mechanical Turk, in which people from different fields collaborate with each other, it is important to determine the expertise of the people in advance in order to determine the best qualified person for the task [23].
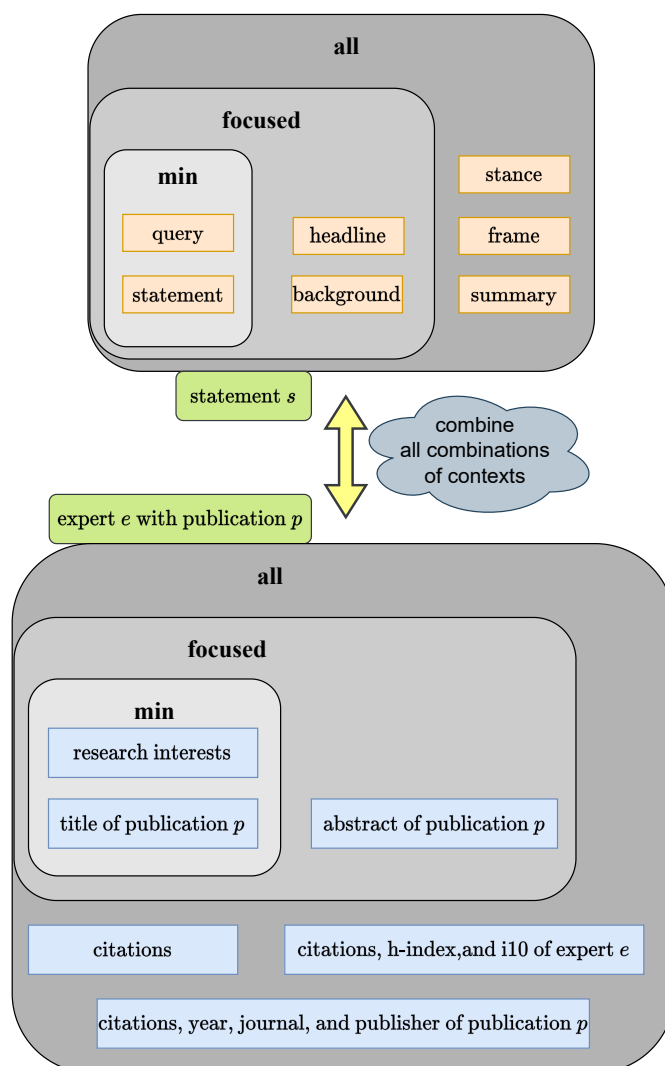
Figure 1: Visualization of the different contexts of the statement as well as the researcher being used to predict the researcher's expertise towards the statement.

3. Task Definition and Dataset

As indicated in Section 1, we aim to estimate a potential expert's domain knowledge with respect to a statement using the context of both the statement and the potential expert. In this section, we first define the new task, then we discuss the dataset we created for this purpose. Note that this construction requires two components: the first consists of statements with their context. The second consists of potential experts and their expertise on these statements.

Task Definition   Given a statement s with context $c(s)$, as well as an expert e with context $c(e)$. The task is to determine whether e is a credible expert given their context $c(e)$, if making
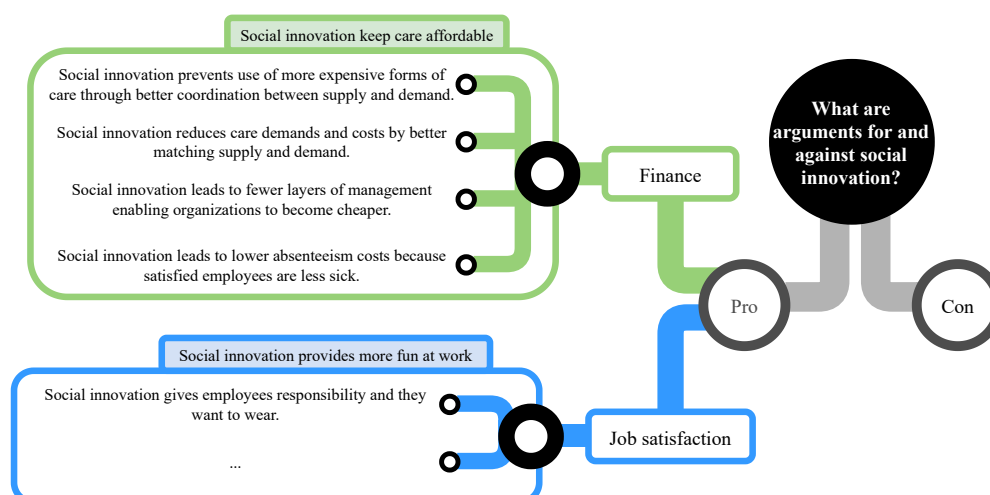
Figure 2: Example of an excerpt of an argument map (from Dumani et al. [24]).

or being cited for the statement s in context $c(s)$. As we restrict our work to researchers, the context $c(e)$ will be represented by e's publications as well as the research interests of e. As in this study we aim to show that our approach is feasible and also to reduce complexity and to anticipate performance reasons, in this paper the expertise of each expert is represented by exactly one of their publications; an extension to all publications will be left for future work.[2] Figure 1 depicts the type of context information we will use for the remainder of the paper. More precisely, we will investigate in all combinations of contexts for both experts and statements. The contexts are split into *min*, *focused*, and *all*. Here, *min* represents the minimum that could be required as context. The set *focused* expands the set *min* with further context that is available, at least for a longer period immutable, and realistic to be used in an application. The last set *all* contains even more context with the goal to examine its impact (1) either with information where the methods to determine are still being researched as in the case with the context of the statement and (2) with data that is rather related to the authority of a researcher as in the case of an expert's publication.

Finding Suitable Statements for our Dataset   We built upon the dataset from Dumani et al. [24] as a source of statements. It consists of 49 argument graphs having 2,186 arguments with binary stances as well as 133 different frames associated with them. This dataset was originally introduced to cluster arguments to different granularities such as their stances, their frames, or their quintessence. Figure 2 shows an example of such a graph that is taken from that paper.

   We chose this dataset for several reasons: first, it covers various (Dutch) national as well as international political issues such as the environment or pensions, on which people might want to listen to expert opinions. Second, since the dataset consists of argument graphs, the root of each graph describes the core question, while each of the other nodes contains further

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[2]We argue that this is not a drawback since in this case an expert would be classified as suitable as long as at least one of their papers fits.

Table 1
Example of a statement with context information.

component	example from dataset
headline	*Infection Prevention*
background	*About this card: This Argumentation Card provides an overview of arguments for or against the implementation of infection prevention measures in all forms of residential care in the elderly. Healthcare professionals have laid down …*
query	*What arguments do nursing homes use for and against implementing infection prevention measures?*
stance	*In front of*
frame	*Feasibility*
cluster	*Infection prevention prevents unnecessary work*
statement	*Caring for sick people takes extra time and is a drain on the daily routine.*

partial information such as the stance, the frame, or a cluster (with a short summary with the quintessence) of the statement. As we aim to incorporate different contexts to each statement in order to evaluate the estimation of expertise, this dataset allows us to do that conveniently. Starting with this dataset, we randomly picked 200 statements with their context information to proceed from there. To avoid bias, we constrained that no statement would be included in this sample if there was already another one with the same stance, the same frame, and consequently the same quintessence. An example of a statement with its context is shown in Table 1.

Enriching the Dataset with Suitable Experts   W.r.t. these 200 statements, three members of our team searched on Google Scholar for two ideal experts for each statement, i.e. researchers who had published papers that are very related to the content of the statements. We decided to use Google Scholar as our expert source as it is the largest scientific literature database of authors and their publications including different disciplines that we are aware of. It includes not only different disciplines, but also different source documents such as professional articles, theses, dissertations, books, abstracts, or court opinions.

The exact task was to find experts for these statements who would be believed if they were cited to substantiate them. In this context, we asked the annotators to find two experts from different papers for each statement, i.e., the expert of paper 1 was not allowed to be a co-author of paper 2 and vice versa.

One annotator proposed experts for statements, and the other two either approved them or replaced them with others that were in turn reviewed by the others. The annotators developed text snippets based on the statements to retrieve suitable experts when typing them into Google Scholar.

In finding the best variation of search snippets, they were allowed to be creative and enter words that do not appear in the sentence. The decision whether an expert was a good match or

not depended on several characteristics, such as the *title* of their publications, their *abstracts*, and their *research interests* which are indicated by the scientist .[3]

From the 200 statements, a total of 340 experts could be determined for 170 statements. The remaining could not be associated with any experts at all, as they are not suitable for verification, e.g. because the statements are far too general, or even far too specific about regional problems.

W.r.t. the example in Table 1, the statement "*Caring for sick people takes extra time and is a drain on the daily routine.*" was changed to the search snippet "*daily effects of caring for sick people*" for which Google Scholar, finds, i.a., the paper titled "*Differences in impact of long term caregiving for mentally ill older adults on the daily life of informal caregivers: a qualitative study*" [25]. In this case, the annotators listed the part "*Caregivers themselves are often aged, and although caregiving implies an impact on daily life that exceeds the boundaries of usual informal care*" of the abstract to be the persuasive part to believe in the expert's knowledge towards that statement.

Rating of Random Scientists to the Statements   Based on these 170 statements and the 340 experts, we randomly picked eight additional experts from this expert pool for each statement, yielding a total of 1,360 additional (statement,expert) pairs. Two annotators independently inspected the researchers' Google Scholar profiles for these pairs and, based on the research interests, as well as their paper titles and abstracts, assigned the labels 0, 1, and 2, indicating whether the researcher is a suitable expert to make the statement. A third annotator also assigned a label if the ratings of the first two differed. This happened 532 times which shows the difficulty of this task caused by the subjectivity of the annotators.

The task was to assume that someone refers for statement s to expert e. Then, the annotators should indicate on the basis of the e's research whether they would be convinced while neglecting the truth content of s, i.e., they just concentrated on the topics of s and the expertise of e.

The label 0 was assigned if the expert did not match the statement at all. This could be, e.g., if the expert is a psychologist, but the statement deals with processors. In contrast to that, the label 2 was assigned if the expert is a perfect fit for the statement. The label 1 was assigned to experts who fit partially. This decision is slightly more difficult to assign because this is more subjective. The annotators were instructed to assign e.g. an economist the score 1, if the statement has something to do with economics. Here we made the assumption that they must have learned the same in their basic studies and are therefore reasonably familiar with each other's subjects. However, obviously, this assumption may not always be correct.

Altogether, we received 3,252 (=2 · 1,360 + 532) assessments for the 1,360 statements. Label 0 was assigned a total of 2,192 times, label 1 a total of 909 times, and label 2 another 151 times.

We measured the robustness of the annotations using Krippendorff's α. Measuring the assessments of the first two annotators resulted in an inter-annotator agreement (IAA) of 0.262 (interval metric). This IAA improved to 0.411 by adding the third annotator. According to Landies and Koch [26], values between 0.4 and 0.6 represent a moderate agreement.

This value is quite low and indicates the difficulty for this task from a completely different point of view, namely the subjectivity in evaluating expertise. We argue that the annotations

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[3]Note that in addition to the expert itself, we include both the search snippets and the text snippets that convinced the annotator in our dataset.

are nevertheless better than a first glance would suggest as the third annotator knew that the two annotators had previously given unequal annotations, and the latter therefore weighed particularly carefully what to assign.

Final dataset   Finally, our dataset consists of a total of 1,700 labeled (statement,expert) pairs, where 340 were labeled with a score of 2 because the associated experts were manually picked for these statements. For the remaining 1,360 pairs, we used majority voting of the three annotators for the final label. Especially in light of the improved IAA, this seemed reasonable. W.r.t. the 1,360 pairs, 997 were assigned with label 0, another 309 were assigned with label 1, and 54 were assigned with label 2.

4. Methods

With the last section introducing a dataset suitable for learning and evaluating the prediction of researcher's expertise, in this section we now present and evaluate methods for accomplishing this.

We examine three approaches: Our main approach bases on a transformer-based and fine-tuned cross-encoder model. In particular, as we want to measure the performance of different contexts (see Section 3), we consider all 9 (=3 · 3) combinations of the subsets { *min*, *focused*, *all*} × { *min*, *focused*, *all*} of contextual information as shown in Figure 1 and explained in Section 3.

The next approach serves as baseline and makes use of the state-of-the-art BERT where the resulting embeddings are classified by several, i.e., seven standard classifiers such as a support vector machine or gradient boosting.

The last approach serves as a comparison and makes use of a classical and very successful IR approach, namely BM25F [27], which is an extension of the famous BM25 method with document structure and anchor text.

Classifiers based on Cross-Encoders   Due to the great success of transformer-based embedding methods, which have brought about great positive impact in the field of NLP, it is appropriate to use a state-of-the-art model for predicting the expertise of researchers with respect to statements. After weighing the advantages and disadvantages of the various frameworks and approaches, our main approach consists of a cross-encoder [28]. Note that unlike bi-encoders, which produce a separate embedding for each text input and then use, for example, the cosine similarity of vectors to measure their similarity, cross-encoders generate an embedding for two simultaneously introduced texts. In our case, one text input consists of the expert's information and its context, and the other text content consists of the statement and its context. Cross-encoders usually perform better than bi-encoders, but have the disadvantage that they can only be used on predefined sets. However, since the set of potential experts is usually manageable and only needs to be updated at longer intervals, we weighed that it is reasonable to apply this approach.

In our experiments, we created 10 folds for this purpose and evaluated them via cross-validation. We employed the python framework SENTENCE-TRANSFORMERS and utilized the model "`roberta-large`". More precisely, we fine-tuned this model for each combination and

each (train,test) fold for 3 epochs always with a batch size of 16. We refer to this method using the cross-encoder with CE_{RoBERTa}.

Baseline utilizing BERT and Standard Classifiers   As a baseline, we trained several standard classifiers. As input, the classifiers received embeddings created with the pre-trained Sentence-BERT model [29] "`all-roberta-large-v1`". To create the input for the classifiers, we computed an embedding vector for the expert's context and an embedding vector for a statement and its context and concatenated them. We applied the Python library SCIKIT-LEARN [30] for initializing and training the classifiers. We utilized the following algorithms in their default configuration for classification: Multi-layer Perceptron (MLP_{RoBERTa}), Nearest Neighbor (KNN_{RoBERTa}), Gaussian Naive Bayes (GNB_{RoBERTa}), Gradient Boosting (GB_{RoBERTa}), Random Forest (RF_{RoBERTa}), Support Vector Machine (SVM_{RoBERTa}) and Logistic Regression (LR_{RoBERTa}).

BM25F   This approach serves as comparison. The intuition behind this is the assumption that the experts' knowledge represented by their textual publications could have textual overlap to a statement or its context. In order to implement the approach with BM25F, we first indexed all experts together with their context information (as shown in Figure 1) using the Java framework APACHE LUCENE. The goal here is to enter a statement and get a list of potentially matching experts. The main difference between BM25 and BM25F is that the latter allows us to add more fields than just one to the query.[4]

We therefore added the fields from the statement's context, which are shown in Figure 1, to the queries. For example, with the combination $min \times min$, we have a total of four search fields, since we look for both the *statement* and the *query* in the *research interests* and the *titles*. When querying the statement, the result is a list of ten experts with scores that are above APACHE LUCENE's internal and default threshold, but do not yet correspond to our labels 1 (partial expert) and 2 (full expert) and thus have to be converted. [5] In order to get the maximum out, we use wildcards for this prediction, i.e., the correct prediction 1 or 2 is automatically assigned to the expert if BM25F lists the researcher in its list. Using this oracle, we are able to detect the upper bound of this approach with more clarity. We coin this method ORACLE$_{\text{BM25F}}$.

5. Evaluation

We measured the performance with precision, recall, F_1, and accuracy. Therefore, we computed these mean average values in a 10 fold cross validation for each context combination. More precisely, the precision is calculated by the fraction of the experts that were predicted as 1 or 2 for which the prediction was correct. Further, the recall is computed by the fraction of the experts labeled as 1 or 2 for which the prediction was correct.[6] To better interpret these values, we also included a method called ZERO in the evaluation that always predicts 0 because

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[4]In the Java framework APACHE LUCENE this is done by using the class `BlendedQuery` [31].

[5]Note that APACHE LUCENE allows to vary the number of maximum results but our experiments with the values 5, 10, 50, and unlimited had no impact at the final results.

[6]Since BM25F can be seen as an oracle, we mapped the values 1 and 2 to a single value to boost its performance.

Table 2
Evaluation showing the mean average precision (prec), recall (rec), F_1, and accuracy (acc) values of the 10 fold cross validation for each statement (s) and expert (e) combination. Values are sorted in descending order by their F_1 values and rounded to three digits after the decimal point.

method	context(s)	context(e)	prec	rec	F_1	acc
CE$_{\text{RoBERTa}}$	*focused*	*all*	**0.783**	0.526	**0.627**	0.760
MLP$_{\text{RoBERTa}}$	min	min	0.625	0.551	0.584	0.725
CE$_{\text{RoBERTa}}$	*all*	*focused*	0.778	0.486	0.576	0.738
CE$_{\text{RoBERTa}}$	*min*	*min*	0.732	0.513	0.573	0.735
KNN$_{\text{RoBERTa}}$	*focused*	*all*	0.693	0.494	0.572	0.725
CE$_{\text{RoBERTa}}$	*focused*	*focused*	0.687	0.447	0.536	0.721
Oracle$_{\text{BM25F}}$	*all*	*focused*	0.401	**0.721**	0.516	0.439
CE$_{\text{RoBERTa}}$	*all*	*min*	0.599	0.383	0.465	0.705
CE$_{\text{RoBERTa}}$	*all*	*all*	0.551	0.314	0.395	0.691
CE$_{\text{RoBERTa}}$	*min*	*focused*	0.532	0.303	0.371	0.687
CE$_{\text{RoBERTa}}$	*focused*	*min*	0.439	0.294	0.349	0.682
GNB$_{\text{RoBERTa}}$	*min*	*all*	0.286	0.428	0.341	0.475
CE$_{\text{RoBERTa}}$	*min*	*all*	0.483	0.280	0.335	0.674
GB$_{\text{RoBERTa}}$	*focused*	*min*	0.518	0.167	0.249	0.624
Oracle$_{\text{BM25F}}$	*all*	*min*	0.402	0.169	0.238	0.552
RF$_{\text{RoBERTa}}$	*focused*	*focused*	0.761	0.137	0.229	0.64
SVM$_{\text{RoBERTa}}$	*focused*	*min*	0.81	0.117	0.2	0.634
LR$_{\text{RoBERTa}}$	*focused*	*min*	0.527	0.084	0.144	0.602
Zero	-	-	0	0	0	**0.764**
Oracle$_{\text{BM25F}}$	{ *min, focused* }	{ *min, focused* }	0	0	0	0.586

this makes up the largest class in our dataset, allowing us to better interpret the results of the evaluation.

Table 2 shows the performance of the examined methods. Note, that we excluded *all* from the expert combinations in the method Oracle$_{\text{BM25F}}$ as it does not make any sense for textual string matching, e.g., to search for the number of citations of a researcher. The values are sorted in descending order according to the F_1 score, since the accuracy alone can be misleading. Going by the accuracy, we get the best performance by always predicting 0 (see method Zero with accuracy 0.764). However, in this case we also obtain 0 for the precision, the recall, and the F_1-score.

The second best accuracy is 0.76 and is obtained with our classifier CE$_{\text{RoBERTa}}$ with the contexts *focused* for statement and *all* for the expert. The accuracy value is almost equal to that of Zero but the other scores in the table show that CE$_{\text{RoBERTa}}$ is much more useful as its F_1 score (0.627) is also the highest, revealing that this approach also provides reasonable results for partially and full experts and not only for non-experts. We also see that while CE$_{\text{RoBERTa}}$ seems to be a precision-oriented approach (0.783) Oracle$_{\text{BM25F}}$ tends to be a recall-oriented method (0.721). W.r.t. the baseline we only show the classifiers with their best performing context combinations. Following the table, the method MLP$_{\text{RoBERTa}}$ produces the second best performance with the contexts *min*, respectively, when using the F_1 score. While the recall of MLP$_{\text{RoBERTa}}$ (0.551)

performs comparably well to the best method $CE_{RoBERTa}$(0.526), $CE_{RoBERTa}$ achieves the better precision (0.783 instead of 0.625) and thus the better F_1-score (0.627 instead of 0.584).

We can infer from the table that $ORACLE_{BM25F}$ performs better the more context we feed into it. Note, that the good performance of $ORACLE_{BM25F}$ probably results from the fact that it works partly as an oracle. Actually, it performs very poorly when it is not fed with *all* statement's context information. The rankings also suggest that the baseline is more sensitive to the context of the statement. $CE_{RoBERTa}$ performs best when providing *focused* context information of the statement and *all* context information of the expert. However, these numbers should be treated with caution, because the performance was boosted by adding publication-independent features such as the h-index. Considering only the textual content of the publication, *all* $\times$ *focused* produces the best and most realistic result when applying cross-encoders. Almost all standard classifiers perform best when the context *focused* is chosen for the statement. Too much information probably has a negative effect here. Regarding the context of the expert, it is a bit more mixed. In particular, it is noticeable that the second best method in the table, $MLP_{RoBERTa}$, performs best only with minimal input in each case. We suspect that the context in the statement loses its impact due to long background information in *focused*. In the future, we consider using automatic summarization methods like T5 [32] or keyword extractors like YAKE [33, 34, 35] to avoid this issue. Also, we would like to investigate how the performance behaves when trying new combinations, such as $all \setminus focused \cup min$.

6. Conclusion and Future Work

Citing putative researchers to strengthen own viewpoints is a widely used means of Fake News. In this paper, we defined the task of assessing a person's expertise towards a statement and showed successfully that we can predict whether a researcher is a partially or fully suitable expert to be cited to believe a statement by fine-tuning a state-of-the-art transformer model. We make the dataset consisting of 1,700 labeled (statement,expert) pairs together with valuable information to train search engines publicly available for further research towards this new task.

As this evaluation can be seen as kick-off, there is obviously room for improvement. For example, in our study we restricted the dataset to researchers that already published in the field of the statement's topic. Further research needs to expand this to other people who can be experts that have not published papers in the fields of the statements' topics but deal with them such as journalists or politicians. In addition to that, we always measured a researcher's expertise by representing them as the content of exactly one publication (and its context). Naturally, future work needs to incorporate multiple publications of a researcher, e.g. to examine whether other similar works are sufficient to predict a researcher's expertise.

Acknowledgments

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