FaxPlainAC: A Fact-Checking Tool Based on EXPLAINable Models with HumAn Correction in the Loop

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ABSTRACT
Fact-checking on the Web has become the main mechanism through which we detect the credibility of the news or information. Existing fact-checkers verify the authenticity of the information (support or refute the claim) based on secondary sources of information. However, existing approaches do not consider the problem of model updates due to constantly increasing training data due to user feedback. It is therefore important to conduct user studies to correct models’ inference biases and improve the model in a life-long learning manner in the future according to the user feedback. In this paper, we present FaxPlainAC, a tool that gathers user feedback on the output of explainable fact-checking models. FaxPlainAC outputs both the model decision, i.e., whether the input fact is true or not, along with the supporting/refuting evidence considered by the model. Additionally, FaxPlainAC allows for accepting user feedback both on the prediction and explanation. Developed in Python, FaxPlainAC is designed as a modular and easily deployable tool. It can be integrated with other downstream tasks and allowing for fact-checking human annotation gathering and life-long learning.

CCS CONCEPTS
• Human-centered computing → User studies; • Computing methodologies → Learning from critiques; Neural networks;

KEYWORDS
interpretable machine learning; data gathering; fact-checking; human-in-the-loop machine learning

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1 INTRODUCTION
Massive amounts of information is produced daily on the Web and social media [5]. However, not all of it is credible, and it is usually beyond the human scope to verify each one manually. Sometimes, non-credible information inadvertently gets propagated by even popular personalities and manages to reach a large audience. In recent times, researchers proposed different fact-checking algorithms [6, 14] and try to automatically flag inaccurate content. However, most of these models are obscured in nature and rely on the explicit supervised data. Even for the models that indeed predict the correctness of claims, a general lack of interpretability inhibits general trust over its utility in general.

Towards this, there have been some recent proposals that create models that are interpretable-by-design approach that generate an explanation along with the actual fact-checking prediction [1, 7, 14]. Specifically, these approaches not only perform fact-checking on a piece of information but also output the evidence/reasons behind the model’s decision in terms of an extractive piece of text with the end-users. Moreover, approaches like Quin+ [8] provides a web front-end to present not only verification of the user’s claim but also the evidence from the web supporting the verification. In such approaches, the interpretable-by-design models serve as the engine of the fact-checking system. Such interpretable-by-design models are, unfortunately, usually trained on datasets with limited size like Fever[13]. Such limited training data introduces a certain bias towards the used dataset. The end-users, therefore, cannot fully trust the model’s prediction or interpretation. They would also have demand to correct the model’s erroneous prediction or explanation. A human intervention, fortunately, is easy to scale up by conducting crowdsourcing tasks [15].

In this paper, we present FaxPlainAC1, the first interpretable open-source fact-checking web front-end that gathers user correction on model’s false prediction/interpretation. Our framework is presented in Figure 1. FaxPlainAC first retrieves documents potentially related to the claim from online encyclopedias, followed

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1https://faxplain.appspot.com/
by fact-checking using the recent interpretable by design approach ExPred [14]. The approach ExPred justifies (support/refute) the claim regarding each document, together with provides evidence supporting the inference (details in Section 2), and at last asks users feedback, or correction by false results, about the model’s prediction and interpretation. FAXPLAINAC is implemented in Python with the objective to assist users with supporting/refuting evidence along with the decision of the model, together with gathering user annotation in fact-checking task. At present, we incorporate ExPred only into our framework. However, our modular design allows us to incorporate different stand-alone interpretable fact-checking algorithms into FAXPLAINAC, so that the benefits of such proposed algorithms become accessible to different stakeholders such as end-users, professional developers, tech companies, etc. For example, one can easily use an interpretable search system [3, 9, 10], or use evidence-gathering mechanisms [4, 11, 12]. We believe such an application will be immensely helpful in developing new sociotechnical systems that rely on automated fact checking.

2 EXPRD: METHOD BACKGROUND

This section explains the idea behind ExPred [14] approach and gives examples from the fact-checking domain. ExPred is a two-phase pipeline interpretable by a design approach that incorporates the task prediction and the rationales.

In the first phase, it learns to extract explanations/rationales from the input document supervised by both task-specific and rationale-based signals under a multi-task learning (MTL) framework. Both predictions and explanations are learned using a common BERT-based encoder. However, separate decoders are utilized for task and explanation extraction. The MTL criteria are the linear combination of both loss for the prediction and explanation task and represented as follows:

$$L_{\text{loss}} = L_{\text{task}} + \lambda L_{\text{exp}}.$$  

where $L_{\text{task}}$ is a standard binary cross-entropy loss and is the loss of the auxiliary prediction task. The $L_{\text{exp}}$ is the explanation loss. Because there are far more non-evidence tokens than evidence tokens in the explanation supervision, the explanation loss is a balanced version of explanation loss, i.e.

$$L_{\text{exp}} = \frac{1}{|t_0|} \text{BCE}(p_0, t_0) + \frac{1}{|t_1|} \text{BCE}(p_1, t_1),$$

where $|t_0|$, $|t_1|$ are the count of the non-evidence/evidence tokens, correspondingly, while BCE$(p_0, t_0)$, BCE$(p_1, t_1)$ are the cross entropy for all non-evidence/evidence tokens.

In the second phase, a separate over-parameterized model is trained for the prediction task only based on the extracted explanations of the first phase. After training the first-phase MTL model, we do inference on the training/validation data once again to emit machine annotated rationales. Then we screen out all such instances, on which the auxiliary prediction branch fails to predict the correct labels. The screening prevents the second-phase model from being polluted by untrustworthy pieces of evidence. Then for the instances left, all tokens corresponding to evidence identified by the phase 1 model are preserved and all non-evidence tokens are replaced by a wildcard token (here we use period ‘.’). Then the second-phase classifier is trained on the masked dataset. This scheme is referred to as predict and explaining (first phase) and then predicting again (second phase). Fig. 2 describes the overall architecture of ExPred. For example, we want to fact check Emma Watson was killed in 1990 based on the document Emma Charlotte Duerrre Watson (born 15 April 1990) is a French-British actress, model, and activist. Born in Paris ... previously. Watson appeared in all eight Harry Potter films from 2001 to 2011, earning worldwide fame, critical accolades, and around $60 million... The first sentence ‘Watson ... (born 15 April 1990)’ suffices to refute the claim.

In the initialization phase of FAXPLAINAC, an ExPred model is pre-trained on the FEVER dataset [13]. In the inference phase, we concatenate the user input statement and the document following the same manner as presented in [14], namely [CLS] statement [SEP] document. The model outputs both justification and explanation.

3 FAXPLAINAC AS AN EXPRD PLUGIN

In this section, we describe the architecture of FAXPLAINAC and the training procedure of ExPred. The web application part is implemented using Python3 with the Flask framework. ExPred model is firstly implemented using Pytorch 1.8.1 and trained on an Nvidia A100. Then the trained model is loaded through the CPU in the Dockers for inference. Figure 1 presents the overall architecture of FAXPLAINAC. This decoupled design guarantees our ExPred model can be interchangeable with other interpretable fact-checking engines. The step-wise usage instruction is as follows:

### 3.1 Overview of Search System

The FAXPLAINAC architecture receives a query from the user. The task of the system is to **support** or to **refute** the claim based on evidence extracted from documents.

#### 3.1.1 Firing Queries

Standard preprocessing steps (stripping, case folding, etc.) are applied to the statement and the FAXPLAINAC plugin issues a Google Programmable Search API to retrieve relevant Wikipedia pages for the given claim through Google JSON API.

#### 3.1.2 Pruning Search Results

The top-ranking search results are collected, and relevant content is extracted from those pages.
with the help of Mediawiki RESTful tool. The end users can tell the system how many articles to be returned. Specifically for our running example, we choose the top three articles since they are the most relevant document for this user input.

3.2 Interpretable Fact-checking

Next, the ExPred model is applied over the statement and each of these three documents. The model either SUPPORTS or REFUTES the claim, along with providing evidence extracted from documents supporting the prediction. A sample result page is shown in Figure 3 for the statement 'Microsoft is a Chinese company'. Here the first document is misleading for the justification since it states companies in China instead of the company Microsoft. The second seems irrelevant to our statement. And the third result states that Microsoft is an American multinational company, which refutes the claim and of which both the prediction and evidence are correct.

3.3 Collecting User Feedback

As mentioned previously, the pre-trained, well-performing model can be erroneous during inference and possibly need to be re-trained on human tutelage: The last column asks users for their feedback. The results agreed by the users (choosing Yes in the column Agree?) are dumped as trustworthy machine-generated evidence, while users being asked for their feedback about the failing results by choosing No and clicking the Next step button. The outcomes of our example corresponds to three different categories of user feedback:

- the first outcome is wrong because it is misleading for the justification. The user can hence choose No for the column Agree? to report the falsely retrieved document;
- the second outcome is irrelevant to the nationality of Microsoft. Again the user can choose No and report the irrelevance;
- the third output is correct. The User can simply choose Yes and there is nothing more to do to this one.

Note that a Wikipedia article is usually too long and might be cumbersome for the users to read-through and later on fully annotate. Also it exceeds the input length limit of the interpretable fact-checking model. Fortunately for the majority of queries, the definition of the related topic is enough for fact-checking. The definition of concepts usually occurs at the beginning of its Wiki page. Hence, we take the first 30 sentences at the beginning of each article by default and display highlighted evidences, together with those non-evidence tokens, if they occurs at the beginning of the article or closely after a piece of evidence. Additionally, a 'show more of this document' button is placed for each article. If the user is sure the article is indeed relevant to the query, but the evidence does not present in the selected sentences, the user can acquire the next (e.g.) 30 sentences from the returned article and update the corresponding outcome.

3.4 Token-level User Feedback

In the final step, we ask users for the following types of feedback on a separate correction page as shown in Figure 4:
Do following documents SUPPORT or REFUTE your following statement:
"microsoft is a chinese company"?
Choose your answer and toggle up/down the words supporting your justification.

You can require more sentences for each document by clicking "show more content...", if the current snippet does not suffice.

since the introduction of economic reforms in 1978, china has become one of the world’s fastest-growing major economies. as of 2016, it was the world's second-largest economy by nominal gdp and largest by purchasing power parity (ppp). china was also the world’s largest exporter and second-largest importer of goods. china is a member of numerous formal and informal multilateral organizations, including the wto, apem, brics, the shanghai cooperation organization (SCO), the bicom and the g 20. a company incorporated in any of china’s special administrative regions is not considered to be incorporated in china, see the corresponding list for companies incorporated in china’s special administrative regions, for further information on the types of business entities in this country and their abbreviations, see "business entities in china". largest firms this list shows firms in the fortune global 500, which ranks firms by total revenues reported before 31 march 2018. only the top five firms (if available) are included as a sample. notable firms this list includes notable companies with primary headquarters located in the country. the industry and sector follow the industry classification benchmark taxonomy. organizations which have ceased operations are included and noted as defunct. see also list of companies of the republic of china (taiwan) list of companies of hong kong list of companies of macau list of largest chinese companies references.

The whole application is at first encapsulated as a docker image and later on deployed on the Gcloud run7. The visualization technique and cloud platform can also be replaced and tailored according to the researcher’s demand.

4 CONCLUSION

In this paper, we present FaxPlainAC, the first open-source framework for gathering human annotations for interpretable fact-checking systems. We leverage the recent interpretable-by-design model ExPred as the back-end model of our fact checking-explanation-feedback web framework. Our decoupled design enables easy integration with other interpretable search systems. Furthermore, one can switch explainable models because of the modular design of the web front-end and the models. The final contribution of our FaxPlainAC is two folds: Firstly, it identifies errors models made on evidence identification or prediction and secondly, it gathers human annotation as correction on the erroneous results. Such human annotations can expand the existing fact-checking datasets and help models to learn from failures.

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7https://cloud.google.com/run
REFERENCES

[1] Jasmijn Bastings, Wilker Aziz, and Ivan Titov. 2019. Interpretable neural predictions with differentiable binary variables. arXiv preprint arXiv:1905.08160 (2019).

[2] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. (2019), 4171–4186.

[3] Zeon Trevor Fernanda, Jaspreet Singh, and Avishek Anand. 2019. A study on the Interpretability of Neural Retrieval Models using DeepSHAP. In Proceedings of SIGIR. 1005–1008.

[4] Helge Holzmann and Avishek Anand. 2016. Tempas: Temporal archive search based on tags. In Proceedings of the 25th International Conference Companion on World Wide Web ’16. 207–210.

[5] Helge Holzmann, Wolfgang Nejdl, and Avishek Anand. 2016. The Dawn of today’s popular domains: A study of the archived German Web over 18 years. In Proceedings of JCDL ’16. IEEE, 73–82.

[6] Neema Kotonya and Francesca Toni. 2020. Explainable Automated Fact-Checking: A Survey. In Proceedings of COLING ’20. 5430–5443.

[7] Tao Lei, Regina Barzilay, and Tommi Jaakkola. 2016. Rationalizing neural predictions. Proceedings of ACL ’16 (2016).

[8] Chris Samarinas, Wynne Hsu, and Mong Li Lee. 2021. Improving Evidence Retrieval for Automated Explainable Fact-Checking. In Proceedings of NAACL. 84–91.

[9] Jaspreet Singh and Avishek Anand. 2019. Exs: Explainable search using local model agnostic interpretability. In Proceedings of the WSDM ’19. 770–773.

[10] Jaspreet Singh and Avishek Anand. 2020. Model agnostic interpretability of rankers via intent modelling. In Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency. 618–628.

[11] Jaspreet Singh, Johannes Hoffart, and Avishek Anand. 2016. Discovering entities with just a little help from you. In Proceedings of CIKM ’16. 1331–1340.

[12] Jaspreet Singh, Wolfgang Nejdl, and Avishek Anand. 2016. Expedition: a time-aware exploratory search system designed for scholars. In Proceedings of SIGIR ’16. 1105–1108.

[13] James Thorne, Andreas Vlachos, Christos Christoudias, and Arpit Mittal. 2018. FEVER: a Large-scale Dataset for Fact Extraction and VERification. In Proceedings of NAACL ’18. 809–819.

[14] Zijian Zhang, Koustav Rudra, and Avishek Anand. 2021. Explain and Predict, and Then Predict Again. In Proceedings of WSDM ’21. 418–426.

[15] Zijian Zhang, Jaspreet Singh, Upwal Gadiraju, and Avishek Anand. 2019. Dissonance between human and machine understanding. Proceedings of the ACM on Human-Computer Interaction 3, CSCW (2019), 1–23.