ABSTRACT
Misinformation such as fake news has drawn a lot of attention in recent years. It has serious consequences on society, politics and economy. This has led to a rise of manually fact-checking websites such as Snopes and Politifact. However, the scale of misinformation limits their ability for verification. In this demonstration, we propose BRENDA a browser extension which can be used to automate the entire process of credibility assessments of false claims. Behind the scenes BRENDA uses a tested deep neural network architecture to automatically identify fact check worthy claims and classifies as well as presents the result along with evidence to the user. Since BRENDA is a browser extension, it facilitates fast automated fact checking for the end user without having to leave the Webpage.

CSCS CONCEPTS
• Information systems → Document representation; • Computing methodologies → Neural networks.

KEYWORDS
fake news detection; neural networks; hierarchical attention

1 INTRODUCTION
Online fake news has become a major societal challenge due to its consequences in real life. For example, there are instances of stock market disruptions, election meddling and mob Lynchings. To address this, several fact checking organizations such as Snopes, Politifact and FullFact have become popular. Typically they employ experts and journalists who perform a tedious task of manually selecting fact check worthy claims made in online news and social media debunking them.

Existing demos (e.g. FactMata [6], FactMata [4, 4] etc) are limiting to the users reading online news, since they have to first identify the claims within the articles, then switch to a different website for fact checking. There are also demos which either do only claim ranking [1] or just list the relevant websites [10]. Moreover, existing demos do not provide any explanation for the claim classifications. There are no existing demos which can jointly identify the claim and fact check them and provide evidence to the support the decision. To address these issues, BRENDA provides the following contributions:

(1) BRENDA facilitates users to do fact checking without leaving the Website. If users are not sure on which claims to fact check, BRENDA can automatically filter fact check worthy claims.

(2) BRENDA can automatically query online evidence via web search engines and verify claims.

(3) BRENDA uses a proven pre-trained deep neural network model coined SADHAN which considers the latent-aspects of the claim to verify its truthfulness.

(4) In addition to classifying the claims, BRENDA also provides evidence snippets highlighting the importance of both words and sentences relevant for classifying the claim using attention weights from the SADHAN deep neural network model [5].

2 RELATED WORK
Most fact-checking websites such as Snopes.com and Politifact.com perform manual fact check. Some automated fact-checking systems such as CredEye [6] are available. However, since CredEye only uses word-level attention, it can only highlight which words were used for classifying a claim. BRENDA on the other hand can provide evidence at both-word level and sentence-level. Moreover, BRENDA can provide evidence w.r.t each aspect such as subject, author and domain of the claim. FactMata is a commercial tool for automated fact-checking, there is no description of the detection algorithm. Moreover, they do not provide any evidence snippets. Grover[9] is another solution which focuses on detecting neural generated fake news. To the best of our knowledge none of these systems are provided as a browser extension which allows users to fact-check without leaving the article they are reading.

There are some browser extensions such as The Factual6, Trusted Times7, and FakerFact8 which claim to support automated fact checking and they are listed in google chrome extension store.
However, there is no research paper or documentation explaining the model they use. Moreover, we could not find any system which can narrow down the claim within the article using fact-check worthiness detection and use that claim to detect fake news.

3 SYSTEM DESIGN
BRENDA follows a client-server architecture and has a frontend and backend module. The frontend is a browser extension and the backend is a python Flask server.

3.1 Frontend: Browser Extension
We develop a browser extension which works with the popular Google Chrome browser. When the user invokes the fact checking by clicking on the browser extension, JavaScript modules are used to retrieve information and details from the web pages and send the query to the server. When the results are returned back from the server, another JavaScript module is invoked to display the results.

3.2 Backend: Server
The server provides a RESTful API for the browser extension. The browser extension sends the URL or claim text chosen by the user to the server. The server then analyzes the claim text first by retrieving relevant articles from the Web via search engines such as Google and analyzes them by applying machine learning models and gives a prediction for the credibility of the claim. A score indicating how credible the claim is based on the evidence found is sent back to the browser. In this section, we explain different parts of the server. The overall block diagram of the server can be seen in Figure 1.

Querying the Web: Given a claim text, we use Google API to retrieve the top-10 relevant web pages. We use the claim text as the query without quotes. Before passing the text to the neural network for credibility prediction, we preprocess the text to tokenize, extract publication date, authors and summary etc using a python library Newspaper3k\(^9\). Since not all parts of the news article are important to classify the claim, we filter the articles with relevant snippets using cosine similarity (inspired by [7]). Then we select all the snippets above 0.75 similarity score for fact checking.

SADHAN Model: In this demo, for the classification of fake news articles and false claims we use a deep neural network coined SADHAN [5]. SADHAN model uses hierarchical neural attention mechanism [8] for learning the representations for both claim text and the evidence news article both at word level and sentence level. As shown in Figure 2, SADHAN takes claim text and a evidence document embeddings as input. Optionally, SADHAN can also take latent aspects such as ‘author’, ‘topic’ and the ‘domain’ etc into account to guide the attention. The aspect attribute vector used in computation of attention at both the word and sentence level comes from latent aspect embeddings for which weights are trained jointly in the model using corresponding aspect attentions. As shown in Table 1, SADHAN outperforms powerful baselines

### Table 1: Comparison of SADHAN with DeClarE models for False claim detection on Snopes and PolitiFact datasets.

| Data    | Model    | True Acc. | False Acc. | Macro F1 | AUC  |
|---------|----------|-----------|------------|----------|------|
| Snopes  | DeClarE  | 68.18     | 66.01      | 67.30    | 72.93|
|         | SADHAN   | 68.37     | 78.23      | 75.69    | 77.43|
| PolitiFact | DeClarE | 60.16     | 80.78      | 70.47    | 80.80|
|         | SADHAN   | 79.47     | 84.26      | 80.09    | 85.65|

\(^9\)https://newspaper.readthedocs.io/
which uses word-level attention such as DeClarE [7]. For more details and performance evaluation of SADHAN see [5].

Claim Detection: Since not all sentences in the articles are worthy of a fact check, we train a classifier and use it for detecting the claim check worthy sentences. We use ULMFiT, a language model fine-tuning technique [2] and use a model inspired by Averaged-SGD-LSTM [3] to train our classifier. The model is trained with a dataset with 9069 labeled sentences (4094 from a presidential debate dataset 10 and 4975 from the Politifact dataset 11. We combined these two datasets and together the dataset has 4666 with label “claim” and 4193 with label “non-claim”. We performed 5-fold cross validation and got a precision of 0.913, a recall of 0.937 and F1-score (micro) of 0.920. We use the softmax value of the model as a claim-check worthiness score for the given sentence.

4 DEMONSTRATION
The screen recording of the demonstration can be found here12. When the user invokes BRENDA, a popup is launched where the user can choose with what method they want to analyze the article. The user can then choose one of the two options, as shown in Figure 3(a). When the “Analyze marked text” is chosen the selected text is used as the claim and sent to the server, which then runs the series of web page extraction, NLP and classification explained in Section 3.2. The result from the SADHAN model is displayed in the same popup window (See Figure 3(b)). The user can also choose to see the evidence by clicking on the “evidence” button, which then extracts the evidence snippet according to the attention mechanism of SADHAN model.

Users can also give a feedback if the model makes a mistake (Figure 3(c)) which in-turn could be potentially used to improve the classifier or evaluate the performance on the live data. When “Analyze

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10https://github.com/apepa/claim-rank/tree/master/data
11politifact.com
12https://www.youtube.com/watch?v=LjaqH5JogGo
Figure 4: Evidence visualization for the claim "Covid-19 can be cured by ingesting disinfectants" using the attention weights

the whole article” is clicked, another popup shown in Figure 3(d) is launched. BRENDA automatically analyzes the whole article and fact checks the top scored claim using SADHAN model. The user can also explore other identified claims in the article by setting the claim score threshold and the top-k sentences. The user can also provide feedback on claim score prediction by our model. When the user clicks on the evidence button, the user can also see the highlighted sentences based on the attention mechanism in SADHAN model [5]. The sentence-level attention weights are aggregated using word-level attention weights. This provides an intuitive understanding of the text the model considered as important for the classification. For example, in Figure 4, for the claim "Covid-19 can be cured by ingesting disinfectants" the evidence is shown with highlighted sentences with contrast of the color proportional to the normalized aggregated word-level attention weights. The Chrome browser extension along with the instructions on how to install it can be found here13.

5 CONCLUSION
In this demonstration we proposed BRENDA which is a browser extension to tackle the challenge of misinformation. The user can use BRENDA to first identify fact check worthy claims in any news article online. Subsequently the user gets the credibility classification using a sophisticated deep neural network model. The users are also presented with the evidence from the model, and can achieve all this without leaving the Web page of the news article they are reading.

REFERENCES
[1] Gencheva, P., Nakov, P., Márquez, L., Barrón-Cedeño, A., Koychev, I.: A context-aware approach for detecting worth-checking claims in political debates. In: Proceedings of the International Conference Recent Advances in Natural Language Processing, RANLP 2017. pp. 267–276 (2017)
[2] Howard, J., Ruder, S.: Universal language model fine-tuning for text classification. arXiv preprint arXiv:1801.06146 (2018)
[3] Merity, S., Krkar, N.S., Socher, R.: Regularizing and optimizing LSTM language models. CoRR abs/1708.02182 (2017)
[4] Miranda, S.a., Nogueira, D., Mendes, A., Vlachos, A., Secker, A., Garrett, R., Mitchel, J., Marinho, Z.: Automated fact checking in the news room. In: The World Wide Web Conference. pp. 3579–3583. WWW ’19, ACM (2019)
[5] Mishra, R., Setty, V.: Sadhan: Hierarchical attention networks to learn latent aspect embeddings for fake news detection. In: Proceedings of the 2019 ACM SIGIR International Conference on Theory of Information Retrieval. pp. 197–204. ICTIR ’19, ACM, New York, NY, USA (2019)
[6] Popat, K., Mukherjee, S., Strötgen, J., Weikum, G.: Credeye: A credibility lens for analyzing and explaining misinformation. In: Companion Proceedings of the The Web Conference. pp. 155–158 (2018)
[7] Popat, K., Mukherjee, S., Yates, A., Weikum, G.: Declare: Debunking fake news and false claims using evidence-aware deep learning. In: EMNLP. pp. 22–32 (2018)
[8] Yang, Z., Yang, D., Dyer, C., He, X., Smola, A., Hovy, E.: Hierarchical attention networks for document classification. In: NAACL: HLT. pp. 1480–1489 (2016)
[9] Zellers, R., Holtzman, A., Rashkin, H., Bisk, Y., Farhadi, A., Roesner, F., Choi, Y.: Defending against neural fake news. In: Advances in Neural Information Processing Systems. pp. 9051–9062 (2019)
[10] Zhu, S., Sun, Y., Liu, J., Zhang, C., Han, J.: Claimverif: a real-time claim verification system using the web and fact databases. In: CIKM. pp. 2555–2558. ACM (2017)