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Explore The Style For Fake News Detection

Wilbert, Hui-Kuo Yang+ and Wen-Chih Peng
Department of Computer Science
National Yang Ming Chiao Tung University
Hsinchu, 300093 Taiwan
E-mail: wilbert.cs08g@nctu.edu.tw;hgyang@gmail.com;wcpeng@cs.nycu.edu.tw

The spread of information on the internet is caused with little to no filters or supervision, which enables the widespread dissemination of misinformation. Due to the frequency of false content, misinformation has been treated synonymously as fake news. To mitigate the fake news problem, we have explored automatic methods to sort through the vast amount of information for its correctness. The problem occurs because fake news is fabricated deliberately to include false information, which is hard to verify. Many general-purpose classifiers rely on content to determine its reliability which unfortunately often could not be verified due to a lack of information about an incident that happens in real-time. The lack of real-time information inhibits the model's ability to produce an educated prediction. In our work, we propose a method that focuses on writing style to generalize the classifiers to maintain robust performance for previously unseen topics and unseen sources. The experiment shows that our model could improve over 5% over the BERT[1] model and over 3% over the best results on documents with unknown sources; our model establishes the best results in the condition where training data is insufficient by improving 5-8% over baseline results.

Keywords: Deep Learning, Fake News Detection, Graph Neural Network, Writing Style, Natural Language Processing.

1. Introduction

News consumption has changed from a traditional method such as newspapers to online devices. The rapid growth of information technology accelerates information sharing in online media and news spreading.[1]. However, this rapid growth is not accompanied by increasing consumer vigilance when consuming media. Online media are usually loosely regulated, and violators are usually not punished. Tech giants have felt increasing scrutiny regarding rampant disinformation that spreads on their platforms, e.g., Google, Facebook, and the US Congress has summoned Twitter for a hearing regarding online platform liability for the

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+Corresponding author
[1]https://www.journalism.org/2021/01/12/news-use-across-social-media-platforms-in-2020/

content that third parties post[2]. Social media companies have taken steps to curb misinformation, but researchers have shown it is still widely present on the platforms. The problem arises due to the sheer amount of information posted on those platforms[3]. Therefore, the need for automation to speed up the preliminary checking is growing over time[2]. Challenges in detecting fake news stem from the lack of a well-labeled dataset and the noisy environment of textual information. Fact-checking-based models tend to tackle the problem with the inclusion of external knowledge[3][4][5]. Huge pre-trained models, such as BERT[1] and others[6][7][8][9] are transformer-based NLP models[10] which demonstrate their capabilities in fake news detection. However, they still possess problems such as domain coverage and real-world deployment. Fake news often has malicious intent to influence its readers. A persuasive writing style then becomes necessary for these goals. Thus, a method to differentiate manipulators and actual truthful publishers by capturing the writing style is developed. The writing style has been an important trait, and one of its earlier applications was author verification [11]. The success of author verification has affected many works. In particular, the trick of unmasking has been applied for genre-style classification concerning fake news [12]. Many statistical methods have been used to approximate stylometry techniques that are usually done by the human checker [13, 14, 12, 15]. The Bag of words has been proven as a simple but effective method for determining writing style by analyzing word usage statistics. Stylometric[15] utilizes the output of Stanford CoreNLP and built the ML method to calculate document credibility. The style information is helpful in fake news detection; however, due to its sole reliance on a simple extraction method, this approach could not generalize well. In our work, we propose a model to explore the writing style for assisting fake news detection. Our contribution is as follows:

- We present the method to explore the style using a Graph Neural Network for fake news detection.
- We propose a model that utilizes only common words in the corpus, which enables the model to focus more on the style information of the news text and minimizes memory usage.
- We improve the generalization ability of the model to classify fake news from unseen topics or unknown sources.

2. Methodology

2.1 The Concept of Style in Model Design

We construct our model to capture the following information of style from news articles: (1) The patterns of neighboring words in an article. (2) n-hop word

[2]https://www.reuters.com/article/usa-congress-tech-idINKBN2BI2M8
[3]https://www.internetlivestats.com/twitter-statistics/

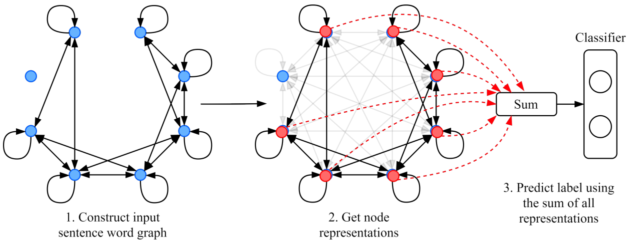

Fig. 1: The framework of the proposed model. The words of input sentences will be represented as nodes in the graph. The model will then calculate node representation using global information and its neighbor embedding. The sum of node embedding will then be fed into a linear layer for prediction.

associations for the pattern of jump reference. (3) Link structure between common and low-frequency words (e.g., keywords, named entities) in an article. (4) The aggregated information of the above patterns. We use these as style information for fake news detection rather than traditional natural language processing artifacts [12, 13, 14, 15], e.g., n-gram word frequency; word counts in a selected set of dictionary, mainly for three reasons. First, their approaches involve much effort in hand-crafted feature engineering and feature selection. Second, such NLP style features could lead to overfitting to particular sources and topics in classifier training [15]. Third, their features limit the model to learning only lexical patterns from word statistics but not the meaning of the words and their co-occurrences.

In our model design, each news article is transformed into a graph, in which nodes are words in an article, and edges link those words of neighboring relations or n-hop associations so that the model can obtain desired style information. We keep a list of common vocabularies of size $|V|$ and replace those words of an article not in the list V with a special token. Instead of increasing the vocabulary size over time for new word addition, we fix the list to contain the most common words for the long-term usability of the model and thus also avoid the issue of out-of-vocabulary in graph formation. With the replacement of a special token, our model could focus on distinguishing the style information of how other words are associated with the named entities or keywords between credible and non-credible news. We incorporate word embedding to leverage the use of vectors that have encoded the meaning of words in a large-sized corpus and update the vectors to reflect the style information by message passing. The updated vectors are aggregated and mapped to a linear layer for training a classifier to detect fake news. Figure 1 shows the high-level overview of the model.

2.2 The Word Graph for Style Information

For each news article, we construct a word graph (N, E), where N and E represent the node set and edge set. The word graph (N, E) is an input to the model, and the node set N only includes words that exist in V. The vocabulary size $|V|$ is limited to the most frequent words in the pre-trained word embedding $Z = \{z_1, z_2, ..., z_{|V|}\}$. The edge in the set E links the nodes in a word graph with

n adjacency in the news article. The model will then traverse each node according to an input article.

Whenever a word in an article does not exist in our vocabulary list, it will be replaced by a particular token, "<UNK>". By the replacement with "<UNK>" token, we can restrict the model to learn different kinds of interactions between common words and "<UNK>" token, which we regard as one of the styles of writing to detect fake news.

Figure 2 shows an example of a constructed graph for the sentence "*when it comes to the success of the electric car, billionaire Elon Musk is viewed as nothing short of a miracle worker.*", where each arrow represents a directed edge between two consecutive words, assuming $|V| = 1,000$ and $n = 1$. Each node represents the original words in the sentence and will be replaced by the "<UNK>" token if it is not in V. We do not remove unknown tokens to enable the model to learn general representations for any uncommon words in the sentence.

Inspired by Unmasking. The idea of the replacement with "<UNK>" is inspired by Unmasking [11, 12]. This trick was applied originally for author verification [11] and was proved fairly robust. It was then extended to distinguish genre style for hyperpartisan articles [12].

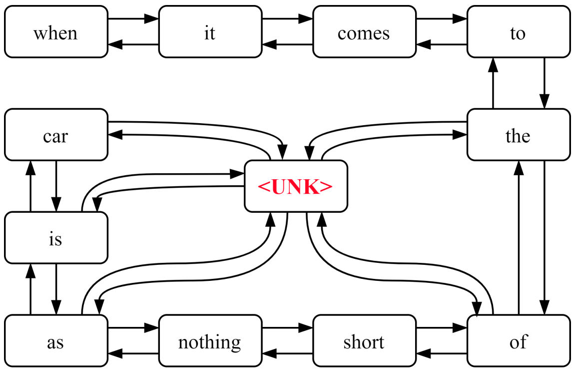

Fig. 2: Example of a word graph.

2.3 Update Node by Style Information

Our graph model could be trained by updating node vectors to improve its global information for the graph. We employ a similar idea to [16] message passing mechanism to update only nodes that occur in the input sentence by style information. The representation of each node in the input is updated by collecting information from each corresponding node's neighboring embeddings. The received messages from neighbors reflect the influence of adjacent words on current words. Then, we introduce non-linearity to the message by applying the max pooling function on each message. Formally, for each node, we calculate the message by:

$$M_j = \max_i h_{ij} z_i \tag{1}$$

where M_j represents the message that will be received by node j. i is the neighbor node for node j with respect to E computed at the word graph construction . h_{ij} is a learnable adjacency matrix, and z_i is the embedding of nodes i. By using the max pooling function, we would like the model to prioritize important information in the representation and discard noise from the message.

Next, we will extract a representation of each node using its embedding and the message that is received from its neighbor. We define node representation as below:

$$r_j = \theta_j M_j + (1 - \theta_j) z_j, \tag{2}$$

where θ is a learnable parameter to control how much information could flow into the target nodes. Figure 3 illustrates the update of node vector with message passing mechanism.

2.4 Predicting Label

We then sum the node representation for each word in the input article:

$$r_A = \sum_{j \in \{k | w_k \in A\}} r_j, \tag{3}$$

where A is the input news article. Using sum in this consideration would preserve the information about document length and the impact of each token on its overall representation.

Next, article representation will be mapped into label probability in output space by a linear layer accompanied by the ReLU activation function:

$$\hat{y} = \mathrm{ReLU}(\mathrm{LinearLayer}(r_A)) \tag{4}$$

Finally, we minimize the cross-entropy loss with log softmax activation between ground truth and predicted logits:

$$loss = -\sum_i y_i \log(\mathrm{softmax}(\hat{y}_i)), \tag{5}$$

where y is the ground truth.

3. Experiment

In this section, we present the experiments of our proposed model to answer the following evaluation questions:

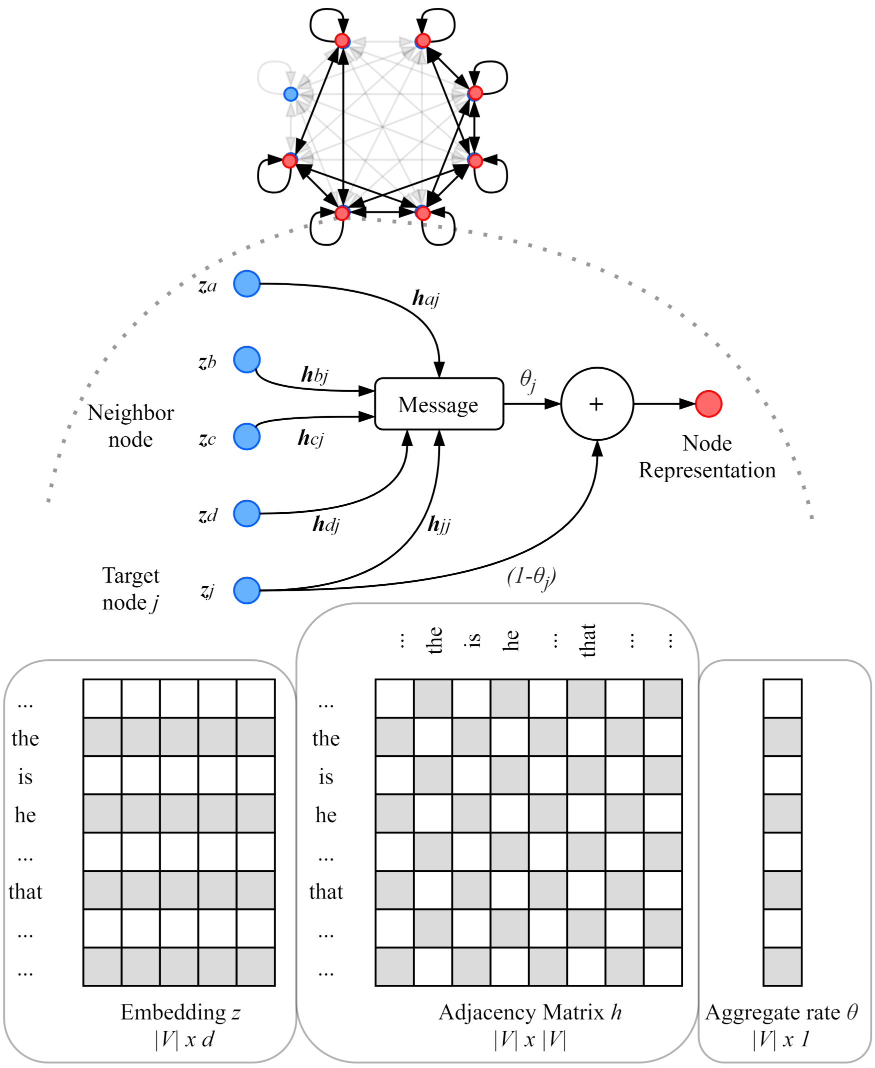

Fig. 3: Example of our message passing mechanism on one of the target nodes.

- **EQ1** Can we improve the fake news classification accuracy when our model is trained with certain style information?
- **EQ2** Can we sustain nearly the same accuracy level when our model is trained with less style information?
- **EQ3** Is the style information extracted by our model sufficient in assisting fake news detection?

3.1 Datasets and Baselines

We utilize the fake news datasets called FakeStyle[4][15]. The statistics of the dataset can be seen in Table 1.

Table 1: The statistics of the FakeStyle dataset

News articles count	97,925
Credible news	46,769
Non-credible news	51,156
Avg. article length (words)	1,004.70
Min. article length (words)	44
Med. article length (words)	680
Max. article length (words)	113,205

The datasets will be split into three scenarios with 5-fold cross-validation (CV) each. The scenario used is as follows:

- **document CV**, a random split of the training and testing set. This scenario is used to show the condition where similar news articles have existed in the training set.
- for **topic CV**, we assign topics into a training and a testing set using LDA topics clustering. Topics in the training set will not be found in the testing set, maintaining its uniqueness.
- for **source CV**, we split the dataset based on the sources of its news articles. In this scenario, we try to simulate the model to focus more on style information even for existing topics across different website sources.

The baseline methods used in our experiments are **Bag of words**, **Stylometric**[15], **BiLSTMAvg**[15], **BERT**[1].

3.2 Implementation Details

We implemented the Bag of words and the stylometric method as in the original paper[15]. We set the LSTM dimension as 100 initialized with word2vec

[4]https://github.com/piotrmp/fakestyle

embeddings trained on the Google News Corpus[5]. The BERT model is "bert-base-uncased" with a maximum of 512 tokens. Our model uses node representation of 300 dimensions initialized with GloVe embedding[17]. Hop size n will be determined in the experiments to show the different performances. Maximum sentence length L is set at 5,000 with a dropout of 0.5. We used the Adam optimizer[18] with a learning rate of 10^{-3} and L2 weight decay of 10^{-4}. The batch size as used in the training step is 32.

3.3 Fake News Detection Performance

To answer **EQ1**, we first compare our model with representative fake news detection models. We utilize accuracy instead of precision or recall to evaluate the performance of fake news detection. The reason for this evaluation is because of the sufficiently balanced class distribution in our dataset.

Table 2: Accuracy of the baseline method and our model in different scenarios

Method	doc. CV	topic CV	source CV
Bag of words	0.9913	0.9886	0.7078
Stylometric	0.9274	0.9173	0.8097
BiLSTMAvg	0.8994	0.8921	0.8250
BERT	**0.9976**	**0.9965**	0.7960
Our Model (n=1)	0.9775	0.9703	0.7996
Our Model (n=2)	0.9789	0.9735	**0.8561**
Our Model (n=3)	0.9790	0.9734	0.8499

From Table 2, both BERT and Bag of words achieve very high accuracy in document CV and topic CV, showing the importance of prior knowledge and keywords, respectively, for BERT and Bag of words. Our model, not relying on any external information during training, reaches almost 98% on document CV which is not directly influenced by writing style. It suggests that our model can capture keywords from embedded global information to generalize well for the scenario. In the source CV scenario, BERT and Bag of words could not generalize well for unknown sources, losing 20-30% of the accuracy compared to another scenario. Source CV scenario is designed to spot the weakness in focusing only on contextual information within the text. Our model outperforms all other baseline methods in source CV with over 85% accuracy, which shows the result of the improvement done by the style-extraction in our model.

Performance of different hop sizes n has been provided, and our model performs the best when $n = 2$. When considering the difference in performance and computation time, we conclude that $n = 2$ is a better choice for most cases.

[5]https://code.google.com/archive/p/word2vec/

3.4 Assessing Impacts of Less Training Data

To answer **EQ2**, we decreased the amount of training data from 80% of the original dataset to only 60%. This experiment means to model a real-life scenario in which discussion in news shifts from time to time, creating a bigger drift in data distribution between training the model and deploying it. We use the testing set to emulate the drifting result in this experiment.

Table 3: Accuracy of the model when using less training data

Method	doc. CV	topic CV	source CV
BiLSTMAvg	0.8756	0.8703	0.8079
BERT	0.9268	0.9216	0.7720
Our Model (n=1)	0.9765	0.9715	0.7996
Our Model (n=2)	**0.9774**	0.9712	**0.8515**
Our Model (n=3)	0.9766	**0.9716**	0.8341

From Table 3, we could see that the performance of our model does not change significantly compared to Table 2. However, this is not true for other baselines models that perform worse. The accuracy of BERT decreases by approximately 7% in this experiment, which shows the importance of sufficient training data even when fine-tuning the language model. Our model shows the importance of common words when dealing with fake news classification problems. Even though our model could not capture sequential information in a news article, it could approximate the credibility only by using common words.

3.5 Assessing Impacts of Different Number of Nodes in the Graph

To answer **EQ3**, we changed the vocabulary size $|V|$ that we used. It equates to reducing and increasing the number of nodes used in our model.

Table 4: Accuracy of model when $|V| = 1,000$ for our model

Method	doc. CV	topic CV	source CV
Our Model (n=1)	0.9615	0.9609	0.7786
Our Model (n=2)	0.9625	0.9617	0.8299
Our Model (n=3)	0.9633	0.9607	0.8517

Accuracy for our model is getting better as the hop size increases, which shows the relation between the hop size and n-gram in the traditional machine learning method. As shown in Table 4, our model performs robustly well for source CV in this extreme case, showing the strength of global information. This condition, however, is not ideal because we would require more hops to achieve similar performance compared to when $|V| = 10,000$.

Table 5: Accuracy of model when $|V| = 30,000$ for our model

Method	doc. CV	topic CV	source CV
Our Model (n=1)	0.9712	0.9625	0.8394
Our Model (n=2)	0.9792	0.9724	0.8209
Our Model (n=3)	0.9809	0.9801	0.8103

For the case where we increase $|V|$ to 30,000, we could observe that it decreased the accuracy of source CV, especially when $n = 2$ and $n = 3$. This is due to the larger pool of nodes to be trained that resulted in some being poorly trained. When vocabulary size increased, we increased the importance of keyword information when predicting fake news. It can be observed from the improved accuracy when $n = 3$ in document CV and topic CV. We will focus more on the source CV, where there is a more significant accuracy discrepancy than the original Table 2. For this case, small hop size performs the best in source CV. It indicates ease of training when using a shorter n-gram for prediction. This trade-off, however, could not improve the performance exceeding the original model with $n = 2$ that achieves 85.61%.

3.6 Case Study

The first article in Table 6 discussing the army is an example of non-credible news. It contains sufficient preliminary information for the reader to accept that it is real news. It is where perpetrators have successfully skewed readers' perceptions by mixing some truth with the data. Therefore, when we mask most of the information with <UNK>, we arrive at harder-to-read news that only focuses on the main context of the discussion. We could observe that non-credible news contains fewer <UNK> words, showing that it tries to target less sophisticated readers who would not fact-check the news themselves. Credible news rarely involves discussion that is too opinionated. This makes the news seem tedious to read, which is not how viral news spreads. We specifically chose an example of credible news that uses negative words, such as "idiosyncratic," in its content to show the strength of our model. Most sentiment-based models would flag this news as fake news as it is a common trait for most fake news. However, our model masked it as <UNK>, which is quite an uncommon word. The actual representation of <UNK> will then be influenced by its neighbor to accommodate further the difference of input sentences. It enables the different positions of the <UNK> token to have a completely different contribution to the prediction of fake news. If the <UNK> token is surrounded by many other <UNK> tokens, then we determine that the writing style of the observed news article often involves rare words and act accordingly. By exploiting this to our advantage, our model could capture style information while avoiding the pitfalls of focusing on the wrong features.

4. Conclusion

We propose a model to focus on style information for fake news detection. We explore the method to represent style information properly, which aims to: 1) improve the generalization ability and accuracy of fake news detection; and 2) provide a method that utilizes a smaller set of vocabulary to reduce computational time when identifying fake news. We apply the approach of passing a message from neighbor nodes to the input nodes to gain their representation in the Graph Neural Network. Training using this method enables each node to update its corresponding embedding while considering global information even with limited vocabulary size. By representing out-of-vocabulary words as <UNK>, we could incorporate and guide information non-related to style to preserve them within the model. Our experiments show strong and stable performance among different scenarios and choices of hyperparameters and show the effectiveness of the proposed method. Our model could perform on a par with BERT in document CV and topic CV while increasing accuracy by 3-5% in source CV.

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Wilbert received his BS in computer science from the National Chiao Tung University, Taiwan, in 2019 and his MS degree from the National Yang Ming Chiao Tung University, Taiwan, in 2021. Currently, he is working as Backend Engineer at Tiktok Pte. Ltd. developing and maintaining Data Platform which enables rich and easy-to-use data-driven approach to analytics within the company.

Hui-Kuo Yang received his BS and MS degrees from the National Chiao Tung University, Taiwan, in 1996 and 1998, respectively. He then joined the Industrial Technology Research Institute, Hsinchu County, Taiwan, as a software engineer. He was involved in e-commerce and location-based projects, where he applied natural language processing for individual intention analysis. He is working toward his PhD in computer science at National Yang Ming Chiao Tung University. His research interests include applications in data mining, and machine learning.

Wen-Chih Peng received his BS and MS degrees from the National Chiao Tung University, Taiwan, in 1995 and 1997, respectively, and his PhD degree in electrical engineering from the National Taiwan University, Taiwan, in 2001. Currently, he is a professor in the Department of Computer Science, National Yang Ming Chiao Tung University, Taiwan. Prior to joining the Department of Computer Science, National Yang Ming Chiao Tung University, he was mainly involved in projects related to mobile computing, data broadcasting, and network data management. He has served as a PC member in several prestigious conferences, such as IEEE International Conference on Data Engineering (ICDE), ACM International Conference on Knowledge Discovery and Data Mining (ACM KDD), IEEE International Conference on Data Mining (ICDM), and ACM International Conference on Information and Knowledge Management (ACM CIKM). His research interests include mobile data management and data mining. He is a member of the IEEE.

Table 6: Examples of Non-credible and Credible news articles.

Non-credible	VIDEO: US Army Artillery Unleash Heavy Fire Support on ISIS Targets - US Herald Battle of Mosul 2016 - US Army Artillery & M142 HIMARS Heavy Fire Support U.S. Army Soldiers conduct fire M777 howitzers and M142 HIMARS during operations to support the Iraqi security forces in the Battle of Mosul. Fire missions are one way the coalition enables the Iraqi security forces to defeat the IS.
$\|V\| = 10,000$	VIDEO: US Army Artillery <UNK> Heavy Fire Support on <UNK> Targets - US Herald Battle of Mosul <UNK> - US Army Artillery & <UNK> <UNK> Heavy Fire Support U.S. Army Soldiers conduct fire <UNK> <UNK> and <UNK> <UNK> during operations to support the Iraqi security forces in the Battle of Mosul. Fire missions are one way the coalition <UNK> the Iraqi security forces to defeat the IS.
$\|V\| = 1,000$	VIDEO: US Army <UNK> <UNK> <UNK> Fire Support on <UNK> <UNK> - US <UNK> <UNK> Battle of <UNK> <UNK> - US Army <UNK> & <UNK> <UNK> <UNK> Fire Support <UNK> Army Soldiers <UNK> fire <UNK> <UNK> and <UNK> <UNK> during operations to support the Iraqi security forces in the Battle of <UNK>. Fire <UNK> are one way the <UNK> <UNK> the Iraqi security forces to <UNK> the IS.
Credible	’My house is like walking into another universe’ - CNN Style This feature is part of ’The Adorned,’ a new series that explores the psychology behind extraordinary style. See more here. American artist Sue Kreitzman believes there’s a lurking, hidden danger surrounding all of us: beige. At 75, the London-based colorphile has fought a lifelong battle against the bland, covering both herself and her apartment in an idiosyncratic, kitsch, spiritual style. From her otherworldly apartment, we follow her to London’s SpitalfieldsMarket as she seeks inspiration on a ””color walk,”” revealing why she chooses to wrap herself in art and how her family feel about her eye-catching attire.
$\|V\| = 10,000$	’My house is like walking into another universe’ - CNN Style This feature is part of ’The <UNK>,’ a new series that <UNK> the psychology behind extraordinary style. See more here. American artist Sue <UNK> believes there’s a <UNK>, hidden danger surrounding all of us: <UNK>. At 75, the London-based <UNK> has fought a <UNK> battle against the <UNK>, covering both herself and her apartment in an <UNK>, <UNK>, spiritual style. From her <UNK> apartment, we follow her to London’s <UNK> Market as she seeks inspiration on a ””color walk,”” revealing why she <UNK> to wrap herself in art and how her family feel about her eye-catching <UNK>.
$\|V\| = 1,000$	’My house is like <UNK> into another <UNK>’ - <UNK> <UNK> This <UNK> is part of ’The <UNK>,’ a new series that <UNK> the <UNK> behind <UNK> <UNK>. See more here. American <UNK> <UNK> <UNK> <UNK> there’s a <UNK>, <UNK> <UNK> <UNK> all of us: <UNK>. At <UNK>, the London-based <UNK> has <UNK> a <UNK> battle against the <UNK>, <UNK> both <UNK> and her <UNK> in an <UNK>,<UNK>, <UNK> <UNK>. From her <UNK> <UNK>, we <UNK> her to London’s <UNK> <UNK> as she <UNK> <UNK> on a ””<UNK> <UNK>,”” <UNK> why she <UNK> to <UNK> <UNK> in art and how her family feel about her <UNK>-<UNK> <UNK>.