Exploring the Community of Model Publishers on TensorFlow Hub

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ABSTRACT

We explore the community of AI model publishers on TensorFlow Hub (TF Hub). While researchers identified the challenges AI model publishers and AI model users faced, little is known about how they interact with each other in an online community. The analysis of the metadata recorded on TF Hub revealed the models that the AI model publishers uploaded. Also, we found out how the models published by the AI model publishers were shared with other people on TF Hub. To our knowledge, this is the first attempt to explore the online community of AI model publishers sharing their models with each other.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in collaborative and social computing**.

KEYWORDS

TensorFlow Hub, online communities, model publishers

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1 INTRODUCTION

Recently, the number of research efforts in artificial intelligence (AI) such as deep learning (DL) and machine learning (ML) has been increasing. The improvement of AI systems is raising new questions about the best way to build fairness and interpretability into AI systems. With many AI models being uploaded and downloaded online, recognizing the actual experiences of AI system users who download and use the models online is essential to accessing the true impact of the AI system's predictions, recommendations, and decisions. Therefore, it is important for AI model publishers and users to share their knowledge, tools, dataset, and other resources with the online community. Some online communities for AI model publishers have been created, such as PyTorch Hub[1], Model Zoo[2], and Hugging Face[3]. TensorFlow Hub[4] (TF Hub) is one of the most useful communities for AI model publishers. Unlike other online communities, TF Hub allows people to upload and download pre-trained models. While previous studies investigated people who create and share video content with each other on online communities, such as vloggers with visual impairments on YouTube [22] and streamers with visual impairments [10], little is known about the online communities that consist of AI model publishers and how they share the models that they have developed on TF Hub.

To address this gap, our research aims to explore the community of AI model publishers on TF Hub by identifying the metadata of model publishers and the models shared by the publishers on TF Hub. Our study makes the following contributions to the CSCW community:

- We explore the community of the AI model publishers on TF Hub.
- We demonstrate that the method of analyzing the metadata of model publishers on TF Hub could be an alternative strategy to understand people sharing models on TF Hub.
- We provide an insight into design technology to support collaborative work among model publishers.

2 RELATED WORK

This section summarizes prior studies on understanding people using and developing AI models and interacting with each other on online communities. We also present the limitations of the prior studies and explain the necessity of further research to support AI model publishers on online communities.

2.1 AI Model Publishers and Users

Several studies focused on understanding AI model publishers and users [3, 5, 19, 20, 26]. Researchers examined the community of programmers developing AI models [3, 19, 20]. Out of the studies,

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[1]https://pytorch.org/hub/
[2]https://modelzoo.co/
[3]https://huggingface.co/
[4]https://tfhub.dev/

Table 1: Top five model publishers' name, type, number of models, and the ratio of the number of models by the total number of models on TF Hub.

Name	Type	# of Models	Ratio (%)
Google	Org	575	49.8
TensorFlow	Org	216	18.7
Sayak Paul.	Ind	101	8.7
DeepMind	Org	86	7.4
Rishit Dagli.	Ind	21	2.8

two conducted an interview study and a survey study, respectively. While Piorkowski et al. conducted interviews with four AI model publishers and reported their challenges of developing the AI models and their methods to overcome those challenges [20], Cai et al. surveyed 645 software developers who have experience in using TensorFlow.js and reported their motivations and challenges of using TensorFlow.js [3]. Other researchers focused on understanding the user experience (UX) designers using AI models [5, 26]. For example, Yang et al. investigated the motivations and challenges UX designers faced when collaborating with professionals in different domains using AI models [26].

2.2 People Interacting with Each Other on Online Communities

Researchers investigated data posted on multiple online communities (e.g., Stack Overflow and Reddit) to understand how programmers [1, 24, 25] and UX designers [13] interact with each other on online communities, respectively. For instance, Treude et al. explored the online community to understand how programmers ask and answer the questions on Stack Overflow [24]. On the other hand, Ahmed et al. not only crawled the data but also examined the people's interaction in the community by conducting surveys of programmers using Stack Overflow. The finding of this study revealed that programmers stopped answering questions on Stack Overflow mainly because of the low-quality questions and duplicated questions [1]. Similarly, to understand how UX designers interact with each other in online communities, Kou et al. focused on analyzing data posted on online communities of UX designers on Reddit. This study showed that members had conversations about the social recognition of UX designers [13].

2.3 Limitations of Prior Studies

Based on the aforementioned studies, we found that little is known about online communities of AI model publishers. Previous studies aimed at understanding the people using AI models, though questions still remain about challenges AI model publishers face when they share models or interact with other people on an online community. Further research would be needed to understand how model publishers interact with people and models on TF models as promoting communication among members on an online community helps improving the quantity and quality of the projects assigned to each member [4, 6]. Thus, this study aims to take the first step to understand the online community of model publishers. In this study, we focused on identifying the metadata of AI model publishers and the characteristics of models shared by the publishers on TF Hub. Based on the findings of this study, we provide insights into building collaborative environments for model publishers.

Table 2: The total numbers of models, categories, architectures, and datasets for each domain on TF Hub.

#	Image	Text	Audio	Video	Total
# of Models	749	344	34	28	1,155
# of Categories	17	10	7	4	38
# of Architectures	86	15	12	12	125
# of Datasets	39	33	10	6	88

3 METHODS

We crawled and analyzed the metadata of the model publishers and model itself, respectively on TF Hub. First, we crawled the model publishers' metadata on TF Hub using Selenium software[5]. The types of model publisher data we acquired are as follows: (1) publisher name, (2) publisher type, (3) publisher description, (4) external website URLs, and (5) the number of models published by the publisher. Each publisher type is categorized as an individual (Ind) or organization (Org). A group of researchers classified publisher types after reading the publisher description. Second, we crawled the model's metadata that model publishers uploaded on TF Hub. Below is a list of types of data we obtained: (1) model name, (2) collection name that the model is included in, (3) publisher name, (4) model format, (5) model domain, (6) model domain category, (7) dataset used in model training, (8) architecture name, and (9) language of the dataset used in model training. A descriptive statistic method was used to summarize the obtained metadata.

4 RESULTS

As of April 5th, 2022, we identified 36 model publishers sharing a total of 1,155 models on TF Hub. Also, we found that each shared model consists of domains, categories, architectures, and datasets.

4.1 Model Publishers on TF Hub

We identified 36 publishers on TF Hub. Twenty publishers were individual type publishers, while 16 were organization type publishers, such as "Google", "TensorFlow", and "DeepMind." The average number of models that the publishers uploaded to TF Hub is 36.1 (standard deviation=107.2). The publisher named "Google" showed the highest number of models uploaded, which is 575 (see Table 1). The high standard deviation indicates that there is a large gap between the number of models uploaded by those who upload more models and those who upload less. Moreover, we discovered that 35 publishers added external website URLs in the publisher description. Twenty-six publishers put website URLs, fourteen put GitHub, nine uploaded LinkedIn, six uploaded Twitter, and two uploaded Kaggle.

[5] https://www.selenium.dev/

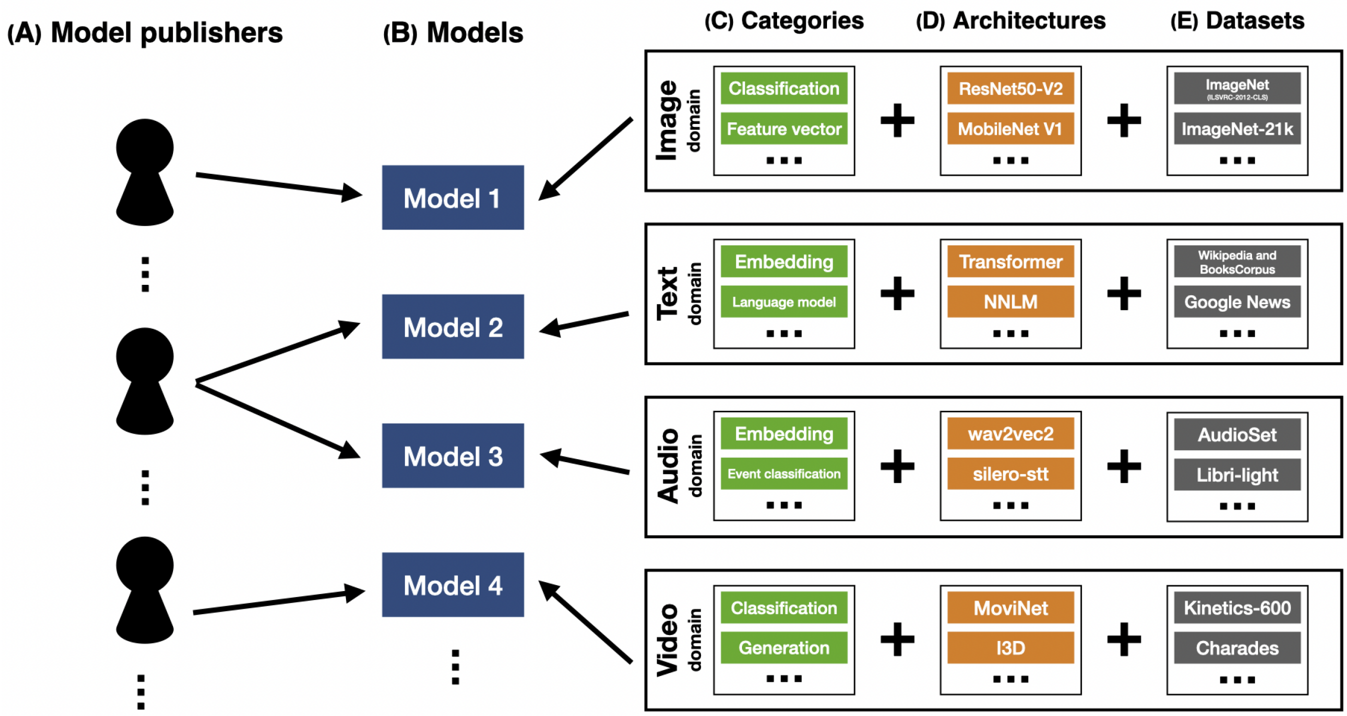

Figure 1: The overview of the relationship between (A) model publishers and (B) models on TF Hub. Model publishers upload one or more models on TF Hub. Each model in the domain is explained with a combination of (C) categories, (D) architectures, and (E) datasets.

4.2 Models on TF Hub

We found 1,155 models and their metadata including model domains, collections, formats, architectures, datasets, and language on TF Hub (see Figure 1). We also identified four domains of models on TF Hub: image, text, audio, and video. Model publishers uploaded 749 models on the image domain, 344 on the text, 34 on the audio, and 28 on the video, respectively. In each domain, models are identified by the combination of category, architecture, and dataset (see Figure 1 (C), (D), and (E)). The number of models, categories, architecture, and dataset for each domain is demonstrated in Table 2. First, the image domain has 17 categories, such as "Classification" and "Feature vector", 86 architectures, such as "ResNet50-V2" and "MobileNet-V1", and 39 datasets, such as "ImageNet (ILSVRC-2012-CLS)" and "ImageNet-21K" [9, 14]. Second, the text domain has ten categories, such as "Embedding" and "Language model", 15 architectures, such as "Transformer" and "NNLM", and 33 datasets, such as "Wikipedia and BookCorpus" and "Google News". Third, the audio domain has seven categories, such as "Embedding" and "Event classification", 12 architectures, such as "wav2vec2" and "silero-stt", and ten datasets, such as "AudioSet" and "Libri-light" [2, 7]. Lastly, the video domain has four categories, such as "Classification" and "Generation", 12 architectures, such as "MoViNet" and "I3D", and six datasets, such as "Kinetics-600" and "Charades" [12].

We identified multiple architectures and datasets used to train models in more than two domains. First, we found that "MobileNet", "VGG Net", and "ResNet" architectures are used to train models in both the image and audio domains [8, 9, 23]. These three architectures are known to be used in training models with transfer learning from image to audio domain [11]. Hence, model publishers may use those architectures to train models in both the image and audio domains. Second, we found that a "Thorsen" dataset is used in both text and audio domains [17, 18]. Puchtler et al. mentioned that this dataset is for text-to-speech model training, so it contains both text and audio dataset [21]. Therefore, it may be possible for model publishers to use this dataset in both text and audio domains.

5 DISCUSSION

The findings of this study revealed about the community of model publishers sharing AI models on TF Hub, though it is questionable about strategies for enabling model publishers to interact with each other actively on TF Hub. Recent studies showed that increasing interactions among users may help increase the number of activities of users on online communities, such as GitHub known as one of the biggest communities of software developers with over 83 million users and over 200 million repositories[6]. For example, Marlow et al. reported that pulling requests help developers find new people on GitHub and decide the way of interaction based on new people's interests and communication styles [15]. Similarly, Feliciano et al. showed that pull requests and issue reports help developers directly contribute to their projects [6]. Furthermore, McDonald and Goggins revealed that pull requests lead GitHub to be more

[6]https://github.com/

transparent, which makes more opportunities for developers to get more reviews and feedback from the community [16].

Also, prior studies showed that enabling visible signs may help developers be more involved in online communities on GitHub. Marlow et al. identified multiple activities of developers, such as presenting their interests by watching and following features, identifying new projects, and looking for new information when receiving new followers [15]. In addition, Dabbish et al. showed that visible actions, such as following and committing history, make developers feel that someone cares about their work and motivate them [4]. Thus, implementing features, such as contributing to the model development and signaling their interests to each other, may help model publishers share models with each other more actively.

6 LIMITATIONS AND FUTURE WORK

This study has several limitations. First, while we identified the metadata of model publishers on TF Hub by crawling the web page data, we did not conduct surveys or interviews to observe behaviors of model publishers, such as motivations for uploading models, challenges they face when publishing models, and strategies to overcome such challenges. Next, we only focused on understanding the community of model publishers. However, there exist two different stakeholders, model publishers uploading models, and model users downloading the uploaded models on TF Hub.

Future work remains to compare an online community of model publishers on TF Hub with other online communities designed for model publishers, such as PyTorch Hub. Also, we may analyze the data not only by using descriptive studies but also by using inferential statistics, such as behavior analysis between model publishers. Moreover, conducting surveys or interviews with model publishers may help better understand the online community of model publishers on TF Hub. Lastly, for better online community building, it would be essential to understand not only the community of model publishers but also the community of model users who download and use the models uploaded by model publishers. For instance, it would be valuable to figure out how much model users would trust the models created by model publishers. In brief, understanding the community of both model publishers and users may help develop a guideline that may enable researchers to build trustworthy large-scale collaboration environments.

7 CONCLUSION

The goal of our study is to contribute to developing an explainable, trustworthy AI community for multiple stakeholders involving both model publishers and users. The primary contribution of this study is to explore model publishers and the models that they uploaded on TF Hub by crawling the metadata on TF Hub. During the process, we identified the features used by model publishers when training the model, such as datasets, architecture, and languages. By identifying these features, we examined the underlying connection between the publishers and the models that they uploaded on TF Hub. Lastly, we suggest a guideline for developing an online AI model community to enhance the usability of model publishers. As for future work, it would be valuable to explore the behaviors of model publishers in different online communities, such as PyTorch Hub, and understand model publishers through surveys and interviews.

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REFERENCES

[1] Tanveer Ahmed and Abhishek Srivastava. 2017. Understanding and evaluating the behavior of technical users. A study of developer interaction at StackOverflow. *Human-centric Computing and Information Sciences* 7, 1 (2017), 1–18.

[2] Alexei Baevski, Yuhao Zhou, Abdelrahman Mohamed, and Michael Auli. 2020. wav2vec 2.0: A framework for self-supervised learning of speech representations. *Advances in Neural Information Processing Systems* 33 (2020), 12449–12460.

[3] Carrie J Cai and Philip J Guo. 2019. Software developers learning machine learning: Motivations, hurdles, and desires. In *2019 IEEE symposium on visual languages and human-centric computing (VL/HCC)*. IEEE, 25–34.

[4] Laura Dabbish, Colleen Stuart, Jason Tsay, and Jim Herbsleb. 2012. Social coding in GitHub: transparency and collaboration in an open software repository. In *Proceedings of the ACM 2012 conference on computer supported cooperative work*. 1277–1286.

[5] Graham Dove, Kim Halskov, Jodi Forlizzi, and John Zimmerman. 2017. UX design innovation: Challenges for working with machine learning as a design material. In *Proceedings of the 2017 chi conference on human factors in computing systems*. 278–288.

[6] Joseph Feliciano, Margaret-Anne Storey, and Alexey Zagalsky. 2016. Student experiences using GitHub in software engineering courses: a case study. In *2016 IEEE/ACM 38th international conference on software engineering companion (ICSE-C)*. IEEE, 422–431.

[7] Jort F Gemmeke, Daniel PW Ellis, Dylan Freedman, Aren Jansen, Wade Lawrence, R Channing Moore, Manoj Plakal, and Marvin Ritter. 2017. Audio set: An ontology and human-labeled dataset for audio events. In *2017 IEEE international conference on acoustics, speech and signal processing (ICASSP)*. IEEE, 776–780.

[8] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. 2016. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*. 770–778.

[9] Andrew G Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, and Hartwig Adam. 2017. Mobilenets: Efficient convolutional neural networks for mobile vision applications. *arXiv preprint arXiv:1704.04861* (2017).

[10] Joonyoung Jun, Woosuk Seo, Jihyeon Park, Subin Park, and Hyunggu Jung. 2021. Exploring the Experiences of Streamers with Visual Impairments. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW2 (2021), 1–23.

[11] Tomoya Koike, Kun Qian, Qiuqiang Kong, Mark D Plumbley, Björn W Schuller, and Yoshiharu Yamamoto. 2020. Audio for audio is better? An investigation on transfer learning models for heart sound classification. In *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. IEEE, 74–77.

[12] Dan Kondratyuk, Liangzhe Yuan, Yandong Li, Li Zhang, Mingxing Tan, Matthew Brown, and Boqing Gong. 2021. Movinets: Mobile video networks for efficient video recognition. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 16020–16030.

[13] Yubo Kou and Colin M Gray. 2018. Towards professionalization in an online community of emerging occupation: Discourses among UX practitioners. In *Proceedings of the 2018 ACM Conference on Supporting Groupwork*. 322–334.

[14] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. 2012. Imagenet classification with deep convolutional neural networks. *Advances in neural information processing systems* 25 (2012).

[15] Jennifer Marlow, Laura Dabbish, and Jim Herbsleb. 2013. Impression formation in online peer production: activity traces and personal profiles in github. In *Proceedings of the 2013 conference on Computer supported cooperative work*. 117–128.

[16] Nora McDonald and Sean Goggins. 2013. Performance and participation in open source software on github. In *CHI'13 extended abstracts on human factors in computing systems*. 139–144.

[17] Thorsten Müller and Dominik Kreutz. 2021. *Thorsten-Voice - "Thorsten-21.02-neutral" Dataset*. https://doi.org/10.5281/zenodo.5525342 Please use it to make the world a better place for whole humankind..

[18] Thorsten Müller and Dominik Kreutz. 2021. *Thorsten-Voice - "Thorsten-21.06-emotional" Dataset*. https://doi.org/10.5281/zenodo.5525023 Please use it to make the world a better place for whole humankind..

[19] Kayur Patel, James Fogarty, James A Landay, and Beverly Harrison. 2008. Investigating statistical machine learning as a tool for software development. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 667–676.

[20] David Piorkowski, Soya Park, April Yi Wang, Dakuo Wang, Michael Muller, and Felix Portnoy. 2021. How ai developers overcome communication challenges in a multidisciplinary team: A case study. *Proceedings of the ACM on Human-Computer Interaction* 5, CSCW1 (2021), 1–25.
[21] Pascal Puchtler, Johannes Wirth, and René Peinl. 2021. Hui-audio-corpus-german: A high quality tts dataset. In *German Conference on Artificial Intelligence (Künstliche Intelligenz)*. Springer, 204–216.
[22] Woosuk Seo and Hyunggu Jung. 2017. Exploring the community of blind or visually impaired people on YouTube. In *Proceedings of the 19th International ACM SIGACCESS Conference on Computers and Accessibility*. 371–372.
[23] Karen Simonyan and Andrew Zisserman. 2014. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556* (2014).
[24] Christoph Treude, Ohad Barzilay, and Margaret-Anne Storey. 2011. How do programmers ask and answer questions on the web?(nier track). In *Proceedings of the 33rd international conference on software engineering*. 804–807.
[25] Yunxiang Xiong, Zhangyuan Meng, Beijun Shen, and Wei Yin. 2017. Mining Developer Behavior Across GitHub and StackOverflow.. In *SEKE*. 578–583.
[26] Qian Yang, Alex Scuito, John Zimmerman, Jodi Forlizzi, and Aaron Steinfeld. 2018. Investigating how experienced UX designers effectively work with machine learning. In *Proceedings of the 2018 designing interactive systems conference*. 585–596.