Investigating Zero- and Few-shot Generalization in Fact Verification

Anonymous ACL submission

Abstract

We explore *zero- and few-shot generalization for fact verification (FV)*, which aims to generalize the FV model trained on well-resourced domains (*e.g.*, Wikipedia) to low-resourced domains that lack human annotations. To this end, we first construct a benchmark dataset collection which contains 11 FV datasets representing 6 domains. We conduct an empirical analysis of generalization across these FV datasets, finding that current models generalize poorly. Our analysis reveals that several factors affect generalization, including dataset size, length of evidence, and the type of claims. Finally, we show that two directions of work improve generalization: 1) incorporating domain knowledge via pretraining on specialized domains, and 2) automatically generating training data via claim generation.

1 Introduction

With a rise in deliberate disinformation, *Fact Verification (FV)* has become an important NLP application. FV aims to verify given claims with the evidence retrieved from plain text. Rapid progress has been made by training large neural models (Zhou et al., 2019; Liu et al., 2020; Zhong et al., 2020) on the FEVER dataset (Thorne et al., 2018), containing more than 100K human-crafted (evidence, claim) pairs based on Wikipedia. Fact verification is also needed in other domains, including news, social media, and scientific documents. This has spurred the creation of a large number of FV datasets, such as COVID-Fact (Saakyan et al., 2021), SciFact (Wadden et al., 2020), and Climate-FEVER (Diggelmann et al., 2020).

However, considering that human annotation is time-consuming, costly, and often biased, it is difficult to collect reliable human-labeled data in every domain that demands fact verification. We need to investigate how to build a generalizable fact verification system that adapts to new domains with zero or few samples. Critically, how can we leverage valuable (evidence, claim, label) annotations from rich-resourced domains (*e.g.*, Wikipedia) to aid fact verification in the low-resourced ones (*e.g.*, scholarly documents, and social media)? Although FV datasets have been recently created in different domains, little analysis has shown whether FV models generalize across them and to what extent existing datasets can be leveraged to improve performance on these new domains.

In this paper, we bridge this gap by conducting an comprehensive investigation of *zero- and few-shot generalization in fact verification*. By conducting a holistic study of FV datasets to date, we first carefully select 8 datasets that have artificial or natural claims, human-annotated evidence, and two or three-classes label for our study. We then standardize their data formats as (evidence, claim, label) pairs and create dataset variants with different granularity of evidence, which gives us a total of 11 datasets. We then conduct a thorough empirical study of generalization and transfer across these 11 datasets. We train models on a source dataset, and then evaluate their performance on a target dataset, either without any additional target training examples (*zero-shot setting*) or with a few additional target examples (*few-shot setting*).

We find that state-of-the-art FV models overfit to the particular training set, generalizing poorly to other datasets. Our in-depth analysis shows generalization is related to several key factors, including dataset size, length of evidence, and the claim type. In particular, we find that Wikipedia-based artificial claims (*e.g.*, FEVER) generalizes well to natural claims in real-world domains with the growth of dataset size, in contrast to prior work that criticized crowd-sourced claims as having strong annotation bias and being unrepresentative of real-world misinformation (Schuster et al., 2019). Our few-shot generalization experiment further shows that fine-tuning on a small amount of target training data

can substantially improve performance.

Armed with the above insights, we explore two ways to improve the generalization of fact verification models. 1) *Domain-specific Pretraining*: initializing the FV model with language models pretrained on specialized domains, and 2) *Data Augmentation*: automatically generating training data for the target domain. Results show that these methods can noticeably improve generalization but still leaves unsolved challenges such as inflexibility, high cost, and label consistency.

To the best of our knowledge, this is the first work to perform a thorough investigation of generalization and transfer in fact verification. We will open source our dataset collection, codes, and models to support future research towards an universal and robust fact verification system.

2 Dataset Curation

In this section, we describe the 11 fact verification datasets included in our study. We first describe the criteria for dataset selection (§ 2.1), and then we introduce the dataset processing (§ 2.2). We show the key characteristics of the datasets in Table 1.

2.1 Dataset Selection

A large number of datasets have recently been introduced to study various tasks for fact checking, *e.g.*, claim detection, evidence retrieval, fact verification, justification production, etc. Our focus, fact verification, in particular, takes a textual *claim* and a piece of *evidence* as input to predict the *label* for the claim. Let's define these aspects:

• **Claim**: Claims for fact verification are often textual, sentence-level statements, which categorized into: 1) *real-world natural claims* crawled from dedicated websites, textbooks, forums, etc. 2) *artificial claims* written by crowd-workers.

• **Evidence**: Evidence is the relevant information source for validating the claim. Textual sources, such as news articles, academic papers, and Wikipedia documents, are one of the most commonly used types of evidence. Based on the granularity, we categorize the evidence in existing datasets into: 1) *document-level evidence* such as the Wikipedia page (Thorne et al., 2018), news articles (Hanselowski et al., 2019), and scientific papers (Wadden et al., 2020). 2) *sentence-level evidence* annotated by human experts in the relevant documents to support or refute each claim. 3) *no evidence* is given for each claim; the model needs to retrieve evidence from a large knowledge source.

• **Label**: The label definition for the claim also varies across datasets. The most common definition is the binary label, *i.e.*, `supports/refutes` and the three-class label, *i.e.*, `supports/refutes/not enough info`. Some works (Wang, 2017; Augenstein et al., 2019) also employ multi-class labels for more fine-grained degrees of truthfulness (*e.g.* true, mostly-true, mixture, etc), where the number of labels vary greatly, ranging from 4 to 27.

Selection Criteria. We employ the following criteria to select the datasets for our study.

• We consider both natural and artificial claims in various domains.
• We consider the datasets with human annotated document-level and sentence-level evidence. We exclude datasets without evidence or which provide only non-textual evidence; *i.e.*, tables, knowledge bases, etc.
• We only consider datasets with the binary or the three-class label annotation due to the difficulty of canonicalizing such multi-class labels.

By conducting a holistic study of fact checking datasets to date, eight different data sources meet our requirements. The full list of candidate datasets we investigate is given in Appendix A.

2.2 Dataset Processing

We then process the selected datasets as follows. 1) We convert each dataset to the unified format of claim-evidence-label triples $(c_i, e_i, l_i)_{i=1}^{N}$. The simplicity of this format allows us to focus on out-of-domain generalization, instead of other orthogonal challenges of fact checking. 2) We create separate dataset variants by pairing each claim with the evidence in different granularity. This enables us to study the impact of evidence length on generalization. After processing, we obtain the final selection of 11 datasets used. We now briefly introduce the nature of each dataset and their specific processing.

Group I: datasets with *artificial* claims. These are based on Wikipedia articles and are often large in size. However, crowd-sourced claims are often written with minimal edits to reference sentences, leading to lexical biases such as the overuse of explicit negation (Schuster et al., 2019).

• **FEVER** (Thorne et al., 2018) asks crowd-workers to mutate sentences from Wikipedia articles to create claims. We use the Wikipedia para-

	Dataset	Domain	Claim	Evidence	Label	# Claims		Avg. # tokens	
						Train	Test	Claim	Evid.
I	FEVER-sent	Wikipedia	artificial	sent-level	S (52%), R (22%), N (26%)	145,327	19,972	9.4	35.9
	FEVER-para	Wikipedia	artificial	doc-level	S (52%), R (22%), N (26%)	145,327	19,972	9.4	368.7
	VitaminC	Wikipedia	artificial	sent-level	S (50%), R (35%), N (15%)	370,653	63,054	12.6	29.5
	FoolMeTwice	Wikipedia	artificial	sent-level	S (49%), R (51%)	10,419	1,169	15.3	37.0
II	Climate-FEVER-sent	Climate	natural	sent-level	S (25%), R (11%), N (64%)	6,140	1,535	22.8	33.8
	Climate-FEVER-para	Climate	natural	doc-level	S (47%), R (19%), N (34%)	1,103	278	22.9	168.9
	Sci-Fact-sent	Science	natural	sent-level	S (43%), R (22%), N (35%)	868	321	13.8	61.9
	Sci-Fact-para	Science	natural	doc-level	S (43%), R (22%), N (35%)	868	321	13.8	257.3
	PubHealth	Health	natural	sent-level	S (60%), R (36%), N (4%)	8,370	1,050	15.7	137.6
	COVID-Fact	Forum	natural	sent-level	S (32%), R (68%)	3,268	818	12.4	82.5
	FAVIQ	Question	natural	doc-level	S (50%), R (50%)	17,008	4,260	15.2	304.9

Table 1: List of the 11 fact verification datasets for our study and their characteristics.

graph associated with each claim as its document-level evidence to construct the *FEVER-para* dataset. We then use the sentence-level gold evidence for the `supports` and `refutes` claims to build the *FEVER-sent* dataset. However, since sentence-level evidence is not available for `NEI` claims, we use the system of Malon (2019) to retrieve the evidence sentences, following Atanasova et al. (2020).

• **VitaminC** (Schuster et al., 2021) creates contrastive evidence pairs for each claim, in which evidence pairs are nearly identical in language and content, with the exception that one supports a claim while the other does not.

• **FoolMeTwice** (Eisenschlos et al., 2021) designs a multi-player game that leads to diverse strategies for crafting claims (*e.g.*, temporal inference) based on Wikipedia, resulting in more complex claims with less lexical overlap with the evidence.

Group II: datasets with *natural* claims. These claims are collected from the Internet and then manually verified by professional fact checkers. They represent real-world claims, and originate from diverse domains, such as scholarly documents, news articles, forums, etc. However, due to the difficulty and high cost of manually verifying real-world claims, these datasets are limited in scale.

• **Climate-FEVER** (Diggelmann et al., 2020) consists of 1,535 real-life claims regarding climate-change collected from the Internet. The top five most relevant sentences from Wikipedia are retrieved as the evidence. Humans then annotate each sentence as supporting, refuting, or not enough information to validate the claim. We use the sentence-level annotation as the evidence for each claim to build the *Climate-FEVER-sent*. We construct the document-level evidence for each claim by putting together all of its evidence sentences, which gives us the *Climate-FEVER-para* version.

• **Sci-Fact** (Wadden et al., 2020) consists of 1.4K expert-written scientific claims paired with evidence-containing abstracts annotated with labels and sentence-level rationale. We use the annotated rationale as the sentence-level evidence to build the *Sci-Fact-sent*. We construct the *Sci-Fact-para* version by using the evidence-containing abstract as the document-level evidence for each claim.

• **PubHealth** (Kotonya and Toni, 2020) contains 11.8K claims accompanied by journalist crafted, gold standard judgments to support/refute the claims. The claims are collected from five fact-checking websites, news headlines, and news reviews. We use the judgement texts as the evidence to pair with each claim.

• **COVID-Fact** (Saakyan et al., 2021) consists of 4,086 claims concerning the COVID19 pandemic crawled from the *r/COVID19* subreddit. We use their sentence-level evidence annotated by crowd-workers as the evidence.

• **FAVIQ** (Park et al., 2021) contains 26k claims converted from natural ambiguous questions posed by real users. The answer-containing Wikipedia paragraph is provided as the document-level evidence for each claim.

Many of the original datasets do not release their test set. Therefore, we use their original split of train/dev sets as our training and evaluation sets. We also standardize the naming of labels as `supports`, `refutes`, and `NEI`. We visualize the global structure of the datasets with tSNE (van der Maaten and Hinton, 2008) and analyze the domain divergence in Appendix B.

3 Zero/Few-shot Generalization

We now explore the generalization ability of fact verification models across the 11 datasets. We first formulate the task of zero/few-shot generalization.

Train↓ Test→	FEVER -para	FEVER -sent	VitaminC	C-FEVER -para	C-FEVER -sent	SciFact -para	SciFact -sent	PubHealth
FEVER-para	—	**72.81**	43.87	20.83	40.90	22.09	28.10	9.05
FEVER-sent	**55.57**	—	**62.11**	44.98	**48.70**	**44.98**	**56.15**	21.61
VitaminC	52.04	65.32	—	42.32	44.40	44.14	50.55	**21.97**
C-FEVER-para	17.86	20.04	10.59	—	42.02	29.93	31.62	5.29
C-FEVER-sent	17.87	24.47	20.25	**54.59**	—	25.84	39.39	8.47
SciFact-para	23.96	27.09	28.37	29.85	28.63	—	44.68	6.78
SciFact-sent	16.86	24.50	29.22	20.61	32.50	29.00	—	4.49
PubHealth	35.21	34.41	30.67	34.12	24.18	40.34	42.03	—
SELF	85.58	89.28	86.76	44.61	62.54	52.25	54.27	72.10

Table 2: Macro-F1 of **3-class fact verification** on the evaluation set for all datasets in a zero-shot generalization setup. Rows correspond to the training dataset and columns to the evaluated dataset. The row SELF corresponds to the in-domain performance (training and testing on the same target dataset).

Task Formulation. Given a claim $\mathcal{C}$ and a piece of evidence $\mathcal{P}$ as inputs, a *fact verification* model $\mathcal{F}$ predicts a label $\mathcal{Y}$ to verify whether $\mathcal{C}$ is supported, refuted, or can not be verified by the information in $\mathcal{P}$. In the *zero-shot generalization* setting, we train models on one source FV dataset, and then evaluate its performance on a target test set, without any additional training data in the target dataset. In the *few-shot generalization* setting, we assume we have a small amount of target training examples.

Fact Verification Model. We use the RoBERTa-large (Liu et al., 2019) as the benchmark model for our study since it has achieved state-of-the-art results in many FV datasets. We concatenate the claim and evidence (`[CLS] claim [SEP] evidence`) and use it as input for a classification task to predict the label of the claim.

3.1 Zero-shot generalization results

Table 2 shows the zero-shot generalization results in macro-averaged F1 for the 3-class fact verification task on all the datasets that have `supports/refutes/NEI` labels, where we partition by dataset group: Group I, top; Group II, bottom. In general, the RoBERTa model generalizes poorly in this zero-shot setup. Compared with the in-domain performance (training and testing on the same dataset), the best zero-shot generalization performance shows a large drop of 20.80% on average. This shows that the FV model overfits to the particular dataset and generalizes poorly to unseen datasets. This validates prior work that show the neural models are brittle when encountering out-of-distribution data. Taking a closer look, we further explore several research questions specific to fact verification behind this general trend.

Do artificial claims and natural claims generalize to each other? The bottom left of Table 2 shows that the model trained on natural claims generalizes badly to datasets with artificial claims, with an average F1 drop of 72% relative to the in-domain performance on the three artificial datasets. In contrast, with natural claims[1], the model generalizes better, with an average F1 drop of 56% (bottom right). This observation supports the argument that artificial claims and natural claims have substantial differences, *e.g.*, Wikipedia vs. real-world domains, high vs. less lexical overlap, and simple vs. diverse reasoning types, as discussed in § 2.2 and related works (Wadden et al., 2020; Saakyan et al., 2021).

However, a surprising and counter-intuitive observation is that the model trained on artificial claims generalize quite well to natural claims. As shown by the top right section, the average F1 drop narrows to 36.9% when generalizing from artificial to natural claims, markedly better than when generalizing between natural claim datasets (56% average drop). In particular, when trained on *FEVER-sent*, the model achieves the best generalization results on 3 out of 5 datasets with natural claims. However, we will show in the following that the large size of artificial claims contribute a lot to its good generalization performance.

Does generalization improve with more data? To examine whether good generalization on the FEVER and VitaminC datasets comes from their large dataset size, we conduct an experiment con-

[1]For fair comparison, we don't count the dataset pairs with the same data source, *e.g.*, (SciFact-sent, SciFact-para)

Train↓ Test→	FEVER -para	FEVER -sent	VitaminC	FoolMe Twice	C-FEVER -para	C-FEVER -sent	SciFact -para	SciFact -sent	PubHealth	COVID -Fact	FAVIQ
FEVER-para	—	**94.91**	71.56	72.50	**77.40**	76.04	72.29	75.92	44.75	56.82	55.09
FEVER-sent	**89.08**	—	**79.79**	84.02	74.71	**80.21**	**75.12**	**87.37**	58.25	63.99	61.64
VitaminC	84.62	94.46	—	**84.57**	62.80	54.59	62.37	69.31	55.32	**70.32**	**62.98**
FoolMeTwice	82.58	91.46	78.56	—	71.38	78.24	69.22	84.19	56.81	58.68	59.23
C-FEVER-para	33.37	33.72	52.56	34.15	—	56.66	39.77	40.89	38.61	25.50	33.52
C-FEVER-sent	51.33	62.00	55.91	50.69	75.85	—	66.72	72.08	55.54	43.04	36.53
SciFact-para	33.38	33.57	46.73	34.42	43.35	49.23	—	41.27	38.69	26.64	33.69
SciFact-sent	33.40	33.64	36.91	33.77	42.63	42.46	44.02	—	43.35	26.64	33.51
PubHealth	65.68	64.69	53.57	53.55	53.92	61.78	68.75	71.01	—	40.95	50.89
COVID-Fact	70.94	76.16	37.22	63.02	44.13	51.71	63.60	76.29	**60.06**	—	46.93
FAVIQ	74.57	73.80	59.14	59.67	64.92	60.49	59.08	52.64	40.15	50.25	—

Table 3: F1 of **binary fact verification** on the evaluation set for all datasets in a zero-shot generalization setup. Rows correspond to the training dataset and columns to the evaluated dataset.

Train↓ Test→	FEVER -sent	Vita minC	C-FEVER -sent	SciFact -sent	Pub Health
FEVER-sent	—	22.20	13.66	19.64	24.57
VitaminC	16.93	—	13.78	20.04	**24.98**
C-FEVER-sent	16.63	8.36	—	17.24	2.51
SciFact-sent	27.43	**26.80**	**30.50**	—	13.06
PubHealth	**28.60**	26.69	18.04	**22.22**	—

Table 4: Macro-F1 of 3-class fact verification for all datasets with sentence-level evidence in a zero-shot generalization setup. *The size of training data is controlled to 800 samples for all datasets.*

Dataset	Zero-shot			In-domain		
	S	R	N	S	R	N
FEVER-para	33.75	**25.85**	34.41	87.05	85.89	**83.81**
FEVER-sent	42.52	**28.24**	44.38	91.32	**89.42**	87.10
VitaminC	50.06	**20.44**	25.96	94.44	89.42	**76.42**
C-FEVER-para	34.14	**24.09**	47.76	68.50	**13.56**	51.76
C-FEVER-sent	28.29	**19.72**	64.00	62.27	**46.40**	78.96
SciFact-para	34.33	**15.35**	51.60	59.29	**23.02**	74.44
SciFact-sent	47.43	**22.23**	55.70	61.87	**18.49**	82.45
PubHealth	20.96	**4.54**	7.79	91.07	82.00	**43.24**

Table 5: Class-wise F1 of 3-class fact verification for the zero-shot generalization setup (left) and the in-domain training setup (right). S: supports; R: refutes; N: NEI.

trolling for data size. Here, we only take 800 examples for each dataset to train the model. We show the zero-shot generalization results between the five datasets with sentence-level evidence in Table 4. The results on all datasets are shown in Table 10 in Appendix C.

We find that the model trained on natural claim datasets (Group I) can generalize to other natural claims slightly better than the model trained on artificial claim datasets (Group II) in this controlled setting. This confirms that dataset size contributes a lot to generalization ability. Tables 2 and 4 together show that Wikipedia-based artificial claims still generalize well to natural claims in real-world domains with the growth of dataset size, although crowd-sourced claims have been criticized to have strong annotation bias and cannot represent real-life misinformation (Schuster et al., 2019).

Which type of label is more difficult to verify? Table 5 shows the break-down of the class-wise F1 score. For each dataset, we show the average class-wise F1 when training the model on other datasets (zero-shot) and the class-wise F1 for training on the same dataset (in-domain). The results show that the `refutes` claim has the worse prediction score (in bold) almost for all datasets, in both the zero-shot and the in-domain setting. The in-domain results are in inline with the empirical observation that (Jiang et al., 2020) it is often ambiguous to differentiate between `refutes` and `NEI` claims even for trained human annotators. This difficulty still maintains in the zero-shot setting and harms the generalization results.

What is the impact of evidence length? From Table 2, we find that fact verification in a dataset with document-level evidence is more difficult than the same dataset with sentence-level evidence (an average of 13.29% drop of in-domain F1). This is understandable, since document-level evidence requires the model to additionally filter out the irrelevant information. Climate-FEVER suffers the largest F1 drop of 31.86%, compared with the slightly performance drop on FEVER (4.3%) and SciFact (3.72%). A possible reason is that

Climate-FEVER's document-level evidence consists of different (even contradictory) evidence sentences, which requires the model to reason over multiple sentences instead of just selecting the most relevant one.

In terms of generalization, the datasets with sentence-level evidence in general achieve better generalization results to other datasets compared to their doc-level versions. For example, C-FEVER-sent generalizes better than C-FEVER-para on 5 of the 6 datasets excluding themselves. Models trained on sentence-level datasets generalize well to other document-level datasets; but the converse is not true. These results indicate that training the FV model on more fine-grained evidence yields better generalization. This is consistent with the intuition that providing fine-grained evidence is eases models' learning in FV, showing the importance of accurate evidence retrieval.

3.2 Zero-shot generalization for binary FV

Many works (Jiang et al., 2020; Saakyan et al., 2021) do not consider `NEI` claims due to their ambiguity. To explore whether our previous observations also hold for the task of *binary fact verification*, we evaluate the generalization results for all 11 datasets using only the `supports` and `refutes` claims for training and evaluation, shown in Table 3. In this setting, artificial claims also generalize well to natural claims in other domains. In 6 of the 7 datasets with natural claims, the best generalization score is from a model trained on artificial claims. This also holds for the evidence length: datasets with sentence-level evidence tend to generalize better than document-level datasets. Finally, compared with the three-class result in Table 2, generalization improves a lot on Climate-FEVER, SciFact, and PubHealth. The reason is that the model struggles in distinguishing between `refutes` and `NEI` claims in these datasets, as reflected by Table 5. Therefore, they benefit a lot from removing the `NEI` label.

3.3 Few-shot generalization results

We now consider the few-shot generalization setting, assuming access to a small number of examples from a target dataset (50 for each class in our experiment). We pre-train a model on a source dataset, and then fine-tune on the target. Our goal is to analyze whether pre-training improves performance compared to training on the target alone.

Train↓ Test→	C-fever -para	C-fever -sent	SciFact -para	SciFact -sent	Pub Health
FEVER-para	50.04	45.99	59.91	68.18	42.81
FEVER-sent	**55.13**	51.84	**66.12**	**76.39**	40.90
VitaminC	50.41	49.80	58.27	68.59	37.84
SELF-few-shot	22.74	10.75	17.24	33.38	43.62
SELF-full	44.61	**62.54**	52.25	54.27	**72.10**

Table 6: Macro-F1 of three-class fact verification for all datasets in a **few-shot generalization setup**.

Table 6 shows the macro-F1 on the evaluation set of all datasets. The row "SELF-few-shot" and "SELF-full" show the performance of directly training on the 150 samples of the target dataset and the full target training set, respectively (without pre-training on the source dataset). In general, pre-training on a source FV dataset and fine-tuning to the target outperforms "SELF-few-shot" on all 5 datasets and "SELF-full" on 3 out of 5 datasets. This shows that pre-training on a related FV dataset helps to reduce the demand for human-annotated training data in the target domain.

Second, *FEVER-sent* obtains good generalization performance in all evaluation datasets. This strengthens our finding in Section 3.1 that FEVER generalizes well to datasets with natural claims in real-world domains. Last, after finetuning, we see dramatic improvement in performance comparing to Table 2. This highlights that current models over-fit to the data they are trained on, and small amounts of data from the target distribution can overcome this generalization gap.

4 Improving Generalization

We then investigate two ways to improve the generalization ability of fact verification: 1) incorporating domain knowledge via pretraining on specialized domains, and 2) automatically generating training data via data augmentation.

4.1 Pretraining on Specialized Domains

In-domain knowledge is essential for fact checking in specialised domains. For example, virology background knowledge is required to verify scientific claims regarding COVID19 (Wadden et al., 2020). When generalizing an FV model from one domain to another, how to endow the model with such in-domain knowledge is a challenging subject worthy of long-term study. Here we explore one simple solution: initializing the model with language models pretrained on specialized domains.

Model	Train↓ Test→	FEVER -para	FEVER -sent	VitaminC	C-FEVER -para	C-FEVER -sent	SciFact -para	SciFact -sent	PubHealth
BERT	FEVER-para	—	64.04	33.82	18.15	29.71	18.53	18.19	3.20
	FEVER-sent	**66.97**	—	**54.75**	35.39	26.49	39.27	39.72	25.95
	VitaminC	54.12	63.28	—	39.57	34.93	40.80	45.51	22.21
BioBERT	FEVER-para	—	67.89	42.41	24.22	38.94	37.69	35.85	8.24
	FEVER-sent	57.18	—	51.95	40.58	39.01	36.83	38.36	37.61
	VitaminC	51.03	60.34	—	**40.60**	**39.72**	43.38	**50.71**	19.44
SciBERT	FEVER-para	—	**68.49**	39.73	20.43	33.84	28.90	35.53	6.37
	FEVER-sent	52.95	—	51.84	35.50	35.68	34.24	39.46	**36.46**
	VitaminC	50.20	58.74	—	37.99	38.79	**43.55**	45.69	20.66

Table 7: Zero-shot generalization performance (macro-F1) when **initialized with different pretraining models**.

In Table 7, we show the zero-shot generalization performance when initializing the FV model with BioBERT (Lee et al., 2020) (pretrained on biology literature) and SciBERT (Beltagy et al., 2019) (pretrained on scholarly documents). Our goal is to explore whether pretraining on specialized domains helps the generalization. To eliminate the impact of other factors such as the model size, we use the BERT model (Devlin et al., 2019) as the baseline, since BioBERT and SciBERT are both based on the BERT model.

We find that BioBERT and SciBERT both outperform the BERT on the generalization scores in Climate-FEVER, SciFact, and PubHealth, with an average improvement of 21.39% and 12.69% in F1, respectively. However, their performance on Wikipedia-based datasets (FEVER and VitaminC) is relatively worse with BERT (-2.6% and -17.7% for BioBERT and SciBERT, respectively). This confirms the generalization of FV in certain domains (*e.g.*, science) can be improved with the language models pretrained on relevant domains (*e.g.*, scientific papers). We have similar observations for the few-shot generalization setting, shown in Table 11 in Appendix D. Despite the positive results, a suitable pretraining model in certain domains (*e.g.*, tweets) is often unavailable. Moreover, this requires re-training the FV model during domain transfer. Therefore, how to develop a more accessible and less expensive way to incorporate in-domain knowledge required for fact checking still requires further investigation.

4.2 Data Augmentation

Another direction we explore is improving generalization via data augmentation, which has recently shown promising results in other NLP tasks such as question answering (Yue et al., 2021) and machine translation (Cheng et al., 2020). We first train a *claim generation* model based on the BART (Lewis et al., 2020), using the (evidence, claim, label) triples *in the source domain* as training data. We use the format `[LABEL] label [NER] NERs [EVIDENCE] evidence` as the input, and use the `claim` as the target output for training, where `NERs` are the entities appearing in the claim (we add `NERs` to guide the model to generate more specific claims). We then apply the trained model to generate claims with different labels in the target domain by separately assigning `supports`, `refutes`, `NEI` as the label prefix of the evidence, and we randomly assign an entity from the evidence as the `NERs`[2] to guide the claim generation. We name this method as **BART-gen**.

We train BART-gen on the *FEVER-sent* dataset and generate synthetic training (evidence, claim, label) triples for other datasets. For each evidence in the target domain, we generate six claims with different (`label`, `NERs`) combinations. Table 8 shows the zero- and few-shot generalization results for BART-gen and other baselines: 1) *FEVER-full*: the model is trained on the original FEVER-sent dataset; 2) *FEVER-control*: the model is trained on a random subset of FEVER-sent which has the same amount of data with the generated data; 3) *BART-gen*: the model is trained on the generated data. For the few-shot setting, the model is further fine-tuned with 150 in-domain samples.

From Table 8, we find that in the zero-shot setting, *BART-gen* consistently improve the generalization performance compared with *FEVER-full* (+24.9% in average) and *FEVER-control* (+47.4% in average). The results show that training with generated target data is in general more effective

[2]Since no ground-truth claim is available for the target domain, the entity cannot come from the claim.

Method↓ Test→	C-fever -para	C-fever -sent	SciFact -para	SciFact -sent	Pub Health
Zero-shot setting					
FEVER-full	44.98	48.70	44.98	**56.15**	21.61
FEVER-control	37.14	45.64	32.42	47.57	20.69
BART-gen	**46.51**	**51.67**	**47.80**	54.63	**69.82**
Few-shot setting					
FEVER-full	**55.13**	51.84	**66.12**	76.39	40.90
FEVER-control	37.17	48.13	62.72	**77.41**	47.03
BART-gen	46.94	**52.80**	50.10	59.00	**70.45**

Table 8: Macro-F1 of three-class fact verification **with data augmentation** (BART-gen) and other baselines.

than directly generalizing a model trained on the source data. This is better reflected by comparing *BART-gen* with *FEVER-control* in which the data amount is the same. The improvement is especially noticeable for *PubHealth*, probably because it lacks the `NEI` claims in its original training set. Data augmentation addresses this by generating a sufficient balanced number of claims for each label.

However, our human evaluation in Appendix E shows that around 30% of generated claims suffer the *label inconsistency* problem, *i.e.*, the BART-gen often generates a fluent claim that does not match our desired label (for example, we want to generate a `refutes` claim, but the generated claim is actually `NEI`). Label inconsistency may introduce conflicting information between the pretraining and fine-tuning stages, which we hypothesize is the cause for the lower level of improvement in fine-tuning the model on the generated data, compared with fine-tuning the model on FEVER. Therefore, although data augmentation is a promising direction to improve generalization, it remains a challenging problem regarding how to generate high quality claims with consistent label.

5 Related Work

To overcome the proliferation of misinformation, a great amount of progress has been made in the area of automated fact verification. For modeling, pretraining-based models (Nie et al., 2019; Stammbach and Neumann, 2019; Zhao et al., 2020; Soleimani et al., 2020) have been used for better text representation and have achieved promising performance. Graph-based models (Zhou et al., 2019; Liu et al., 2020; Zhong et al., 2020) are used to facilitate the reasoning over multiple pieces of evidence. However, most existing models rely on large-scale in-domain training data, which is often unrealistic for every domain that demand fact checking. In this paper, we aim to address this by working towards a generalizable fact verification system that can adapt to different domains with zero or few samples in the target domain.

For datasets, various fact-checking datasets representing different real-world domains are proposed, including both naturally occurring (Augenstein et al., 2019; Gupta and Srikumar, 2021; Saakyan et al., 2021) and human-crafted (Thorne et al., 2018; Sathe et al., 2020; Schuster et al., 2021) fact-checking claims. While these FV datasets focus on different domains, there is still a substantial overlap in the abilities required to verify claims across these datasets. However, little analysis has been done on whether they generalize to one another, and the extent to which existing datasets can be leveraged for improving performance on new ones. Similar studies have been done in other NLP tasks (Talmor and Berant, 2019; Hardalov et al., 2021), while it is less investigated in fact verification. In this paper, we bridge this gap by conducting a comprehensive study of generalization and transfer across existing FV datasets, revealing several key factors for better generalization.

6 Conclusion and Future Work

In this work, we perform a thorough empirical investigation of zero- and few-shot generalization over 11 fact verification datasets. Moreover, we conduct an exhaustive analysis and highlight the most important factors influencing the generalization performance. We further empirically explore two ways to improve generalization in fact verification. We highlight several practical takeaways:

- Overall, the FV model generalizes poorly to unseen datasets compared with in-domain evaluation. However, performance is largely improved by fine-tuning on the target data.
- Artificial claims can also generalize well to natural claims with an increase of dataset size.
- Model trained on sentence-level evidence generalize better than document-level evidence.
- The `refutes` claims are the most difficult to verify among the three labels.
- Domain-specific pretraining and data augmentation consistently improves generalization performance, but they also leave unsolved challenges.

In future work, we plan to experiment with more datasets, including non-English ones. We will also explore the generalization of other sub-tasks in fact checking, *e.g.*, claim detection, evidence retrieval.

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Dataset	Domain	Claim	Doc-level evidence	Sent-level evidence	NEI claims	Publicly available
FEVER (Thorne et al., 2018)	Wikipedia	artificial	✓	✓	✓	✓
WikiFactCheck (Sathe et al., 2020)	Wikipedia	artificial	✓	✓		✓
HOVER (Jiang et al., 2020)	Wikipedia	artificial	✓	✓		✓
VitaminC (Schuster et al., 2021)	Wikipedia	artificial	✓	✓	✓	✓
Fool Me Twice (Eisenschlos et al., 2021)	Wikipedia	artificial	✓	✓		✓
CREAK (Onoe et al., 2021)	Commonsense	artificial	✓			✓
CreditAccess (Popat et al., 2016)	News	natural	✓	✓		✓
Emergent (Ferreira and Vlachos, 2016)	Emergent	natural	✓	✓	✓	✓
MultiFC (Augenstein et al., 2019)	Multiple	natural			✓	✓
Snopes (Hanselowski et al., 2019)	News	natural	✓	✓	✓	
Climate-FEVER (Diggelmann et al., 2020)	Climate	natural	✓	✓	✓	✓
SciFact (Wadden et al., 2020)	Scientific	natural	✓	✓	✓	✓
PubHealth (Kotonya and Toni, 2020)	Health	natural	✓	✓	✓	✓
COVID-Fact (Saakyan et al., 2021)	Forum	natural	✓	✓		✓
X-Fact (Gupta and Srikumar, 2021)	Multiple	natural	✓		✓	✓
FaVIQ (Park et al., 2021)	Forum	natural	✓	✓		✓

Table 9: A list of candidate fact verification datasets.

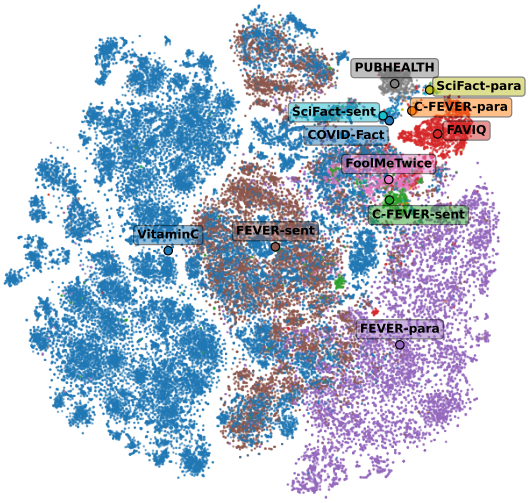


Figure 1: tSNE plot of `[CLS]` representations of each dataset; highlighted points denote cluster centroids.

A A List of Fact Verification Datasets

In Table 9 we provide a comprehensive list of candidate datasets that we consider for our study, including those are not selected in our benchmark in the end. The candidate list does not include the fact checking datasets without providing evidence for the claim (*e.g.*, FakeNewsNet (Shu et al., 2020)), or focusing on non-textual evidence such as table (*e.g.*, FEVEROUS (Aly et al., 2021) and TabFact (Chen et al., 2020)).

Afterward, we exclude some datasets from the candidate list, mainly because of the lack of clean evidence, the small scale in size, non-English claims, and unavailability. For example, we exclude Emergent (Ferreira and Vlachos, 2016) since it only contains 300 claims. We exclude X-Fact (Gupta and Srikumar, 2021) since it is a multi-lingual dataset that mainly focus on non-English languages. Snopes (Hanselowski et al., 2019) is not included since it is not publicly available. We also exclude CREAK (Onoe et al., 2021), HOVER (Jiang et al., 2020), and MultiFC (Augenstein et al., 2019) since their evidence is either coarse-grained (*e.g.*, the whole Wikipedia page) or noisy (*e.g.*, the original webpage in certain fact checking website).

B Domain Divergence Analysis

Following Hardalov et al. (2021), we plot the 11 datasets in a latent vector space to visualize the global structure of the datasets. We proportionally sample 82K (10%) examples, and we pass them through a RoBERTa-large (Liu et al., 2019) model without any training. The input has the following form: `[CLS]` *claim* `[SEP]` *evidence*. Next, we take the `[CLS]` token representations, and we plot them in Figure 1 using tSNE (van der Maaten and Hinton, 2008). We can see that datasets with *natural claims* are grouped top-right, clearly

Train↓ Test→	FEVER -para	FEVER -sent	VitaminC	C-FEVER -para	C-FEVER -sent	SciFact -para	SciFact -sent	PubHealth
FEVER-para	—	**31.98**	27.58	32.83	25.22	**25.36**	30.72	18.82
FEVER-sent	16.68	—	22.20	21.78	13.66	20.01	19.64	24.57
VitaminC	16.70	16.93	—	22.01	13.78	20.04	20.04	**24.98**
C-FEVER-para	17.15	18.00	27.51	—	**31.44**	17.24	18.19	5.04
C-FEVER-sent	16.63	16.63	8.36	17.51	—	17.24	17.24	2.51
SciFact-para	**30.66**	30.66	**28.30**	**33.46**	31.36	—	**42.40**	12.15
SciFact-sent	28.37	27.43	26.80	27.93	30.50	24.51	—	13.06
PUBHEALTH	26.77	28.60	26.69	28.25	18.04	22.80	22.22	—
SELF	32.35	16.68	29.53	36.12	26.14	53.33	50.72	52.05

Table 10: Macro-F1 of **3-class fact verification** on the evaluation set for all datasets in a zero-shot generalization setup. The size of training data is controlled to 800 samples for all datasets. Rows correspond to the training dataset and columns to the evaluated dataset. The row SELF corresponds to the in-domain performance (training and testing on the same target dataset).

separated from those with *artificial claims*. The clusters of real-world domain datasets do not overlap, which highlights the rich diversity of our selected datasets. We also notice that datasets with *sentence-level* evidence have little overlap with their *paragraph-level* counterparts (e.g., Climate-FEVER-sentence v.s. Climate-FEVER-paragraph). To sum up, Figure 1 confirms that there exists divergence between different domains and datasets.

C Full Results of Controlled Size Generalization

Table 10 shows the full results of the controlled experiment in Section 3.1 where we only take 800 examples for each dataset to train the model. We find that the model trained on artificial claim datasets generalize slightly worse to natural claims compared with the model trained on artificial claim datasets in the controlled size setting. Compared with the good generalization results from artificial claims to natural claims in Table 2, it shows that the size of the source dataset contributes a lot to generalization ability of fact verification.

D Full Results of Few-shot Generalization

In Table 11, we show the few-shot generalization performance of FV model pretrained on specialized domains. After finetuning, we observe dramatic improvement in performance comparing to Table 7 (+14.31% for BERT, +11.84% for BioBERT, +15.29% for SciBERT). Under few-shot setting, we find that BioBERT and SciBERT still outperform the BERT on the generalization scores in all datasets except Climate-FEVER-sentence.

E Human Evaluation of Generated Claims

We conduct the human evaluation on the claims generated by *BART-gen* on four datasets: Climate-FEVER-sentence, Sci-Fact-sentence, PubHealth, and COVID-Fact. We randomly sample 90 generated claims for each dataset with a balanced desired label distribution. To be specific, 30/30/30 of their *desired labels*, *i.e.*, the type of claim we expect the model to generate (by appending the corresponding label prefix) are `supports`/`refutes`/`NEI`. We ask two expert human annotators to annotate the *actual label* for each claim, *i.e.*, whether the generated claim is supported, refuted, or cannot be verified by the evidence. If the generated claim is an incomplete or unreadable sentence, we label it as `Unclassified`.

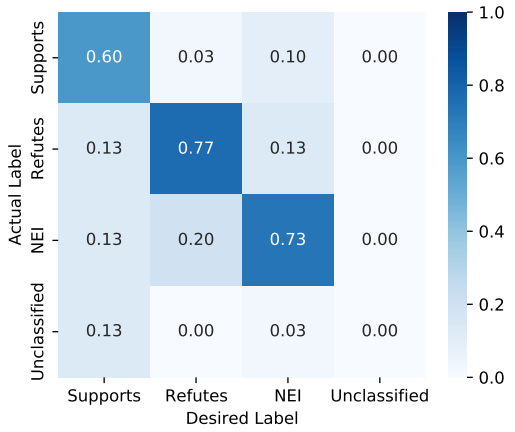
Figure 2 shows the confusion matrix for the desired labels and the actual labels. We find that in all four datasets, around 30% of the generated claims suffer from the *label inconsistency* problem, *i.e.*, the actual label of the claim is not the desired label. Specially, the confusion between the `refutes` and `NEI` claim is the major type of error, showing that `refutes` and `NEI` claims are the hardest for the model to generate.

We also observe that around 5% of the generated claims are incomplete or unreadable. Moreover, most generated claims are short and simple (e.g., "*Gilbert Rothschild was a person*"), which do not require complex reasoning to verify. It is therefore worthy to investigate how to obtain high-quality claims in data augmentation for better generalization in the future study.

Model	Train↓ Test→	C-FEVER -para	C-FEVER -sent	SciFact -para	SciFact -sent	PubHealth
BERT	FEVER-para	41.24	42.68	42.74	43.42	15.57
	FEVER-sent	43.84	**45.09**	50.23	55.65	33.45
	VitaminC	45.94	43.38	57.25	58.12	33.69
BioBERT	FEVER-para	46.22	43.06	**61.45**	59.19	33.47
	FEVER-sent	47.64	43.43	48.59	53.17	39.44
	VitaminC	44.16	40.48	54.52	**61.62**	32.29
SciBERT	FEVER-para	**47.92**	40.46	53.12	56.83	34.39
	FEVER-sent	43.92	40.94	56.53	60.49	**42.14**
	VitaminC	46.23	40.16	60.95	61.04	37.37

Table 11: Few-shot generalization performance (macro-F1) when **initialized with different pretraining models**.

(a) Climate-FEVER-sentence



(b) SciFact-sentence

(c) PubHealth

(d) COVID-Fact

Figure 2: Confusion matrices (normalized over columns) of generated claims on four datasets. The desired label is the input label for our claim generation model (BART-gen) and the actual label is the human-annotated label. "Unclassified" means that the generated claim is incomplete or unreadable.