

FarsTail: A Persian Natural Language Inference Dataset

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Soroush Faridan

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Natural Language Inference

The goal of NLI is to determine the inference relationship between a premise (p) and a hypothesis (h).

Premise	Hypothesis	Label
It's raining	The ground is wet	Entailment
It's raining The sky is sunny		Contradiction
It's raining	The wind is blowing	Neutral

Applications of NLI

- 1. Question answering
- 2. Semantic search
- 3. Automatic summarization
- 4. Evaluation of machine translation systems

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FarsTail: A Persian Natural Language Inference Dataset

Why is this dataset needed?

- 1. The dramatic growth of Natural Language Processing
- 2. Little attention to the inference task in Persian language
- 3. Existence of special complications in Persian language

FarsTail is the first large textual dataset in Persian for the Natural Language Inference task.

It was prepared by a team of six for 22 months.

The data generation scenario is a bit like the SciTail [1] dataset.

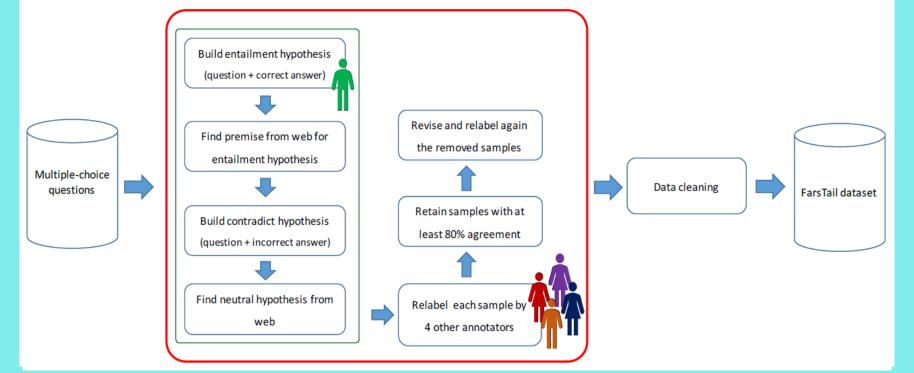
[1] Khot, T., Sabharwal, A., & Clark, P. (2018). Scitail: A textual entailment dataset from science question answering. In Thirty-Second AAAI Conference on Artificial Intelligence.

Textual datasets for the NLI task

Dataset Name	Year of publication	Number of data	
SICK	2014	10,000	
SNLI	2015	570,000	
MultiNLI	2018	433,000	
SciTail	2018	27,000	
XNLI	2018	112,500	

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Development steps of FarsTail dataset



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Example of generating instances

Multiple-choice question:

دبير كل سازمان ملل متحد قبل از أنتونيو گوترش چه كسى بود؟

- خاویر سولانا
 بان کی مون (جواب صحیح)

Who was the Secretary-General of the United Nations before António Guterres?

- Javier Solana
- Ban Ki-moon (correct answer)
- Kofi Annan
- Yoshirō Mori

Entailment hypothesis (question + correct answer):

دبیر کل سازمان ملل متحد قبل از آنتونیو گوترش، بان کی مون بود.

Ban Ki-moon was the Secretary-General of the United Nations before António Guterres.

Premise (from web):

مجمع عمومي سازمان ملل متحد رسماً أنتونيو گوترش را يعنوان دبيركل بعدي سازمان ملل متحد و جانشين بان كي مون انتخاب كرد.

The United Nations General Assembly formally elected António Guterres as the next UN Secretary-General and Ban Kimoon's successor.

Contradiction hypothesis (question + incorrect answer):

كوفي عنان بيش از آنتونيو گوترش بعنوان دبير كل سازمان ملل متحد انتخاب شده بود.

Before António Guterres, Kofi Annan had been selected as the United Nations Secretary-General.

Neutral hypothesis (from web):

اعضاى سازمان ملل متحد به اتفاق آرا أنتونيو گوترش را بعنوان نامزد دبير كلى سازمان ملل متحد معرفي كردند.

The United Nations members unanimously nominated António Guterres as UN Secretary-General.

Statistics of the FarsTail dataset

subset	class	samples	prem. tokens	hyp. tokens	prem. proc. tokens	hyp. proc. tokens	overlap	proc. overlap
Train	E	2,429	40.50	15.53	19.35	8.42	0.67	0.68
	\mathbf{C}	2,389	40.23	15.61	19.20	8.30	0.57	0.54
	N	2,448	40.52	15.62	19.31	8.26	0.40	0.30
	Total	7,266	40.42	15.59	19.29	8.33	0.55	0.51
Val	E	515	39.70	14.85	19.13	8.27	0.67	0.66
	\mathbf{C}	499	39.58	15.09	19.17	8.11	0.58	0.54
	N	523	39.71	14.95	19.16	8.06	0.39	0.29
	Total	1,537	39.67	14.96	19.15	8.14	0.54	0.50
Test	E	519	39.57	15.48	18.84	8.39	0.68	0.68
	$^{\rm C}$	510	39.44	15.81	18.86	8.38	0.57	0.52
	N	535	39.23	16.02	18.73	8.36	0.38	0.27
	Total	1,564	39.41	15.78	18.81	8.38	0.54	0.49

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Results

Model	Representation	Val Accuracy	Test Accuracy	
	tf-idf	0.5303	0.5301	
	LASER	0.5459	0.5198	
SVM	word2vec	0.5120	0.5448	
	fastText	0.5296	0.5371	
	ELMo	0.5621	0.5710	
	word2vec	0.5172	0.5243	
LSTM	fastText	0.5205	0.5192	
	ELMo	0.5478	0.5505	
	word2vec	0.5192	0.5224	
BiGRU	fastText	0.5211	0.5243	
	ELMo	0.5582	0.5428	
DecompAtt	word2vec	0.6597	0.6662	
ESIM	fastText	0.7033	0.7116	
HBMP	word2vec	0.6617	0.6604	
ULMFiT	Learned	0.7281	0.7244	
BERT	ParsBERT	0.8081	0.8299	
DEKI	mBERT	0.8263	0.8338	

Dataset bias by pointwise mutual information

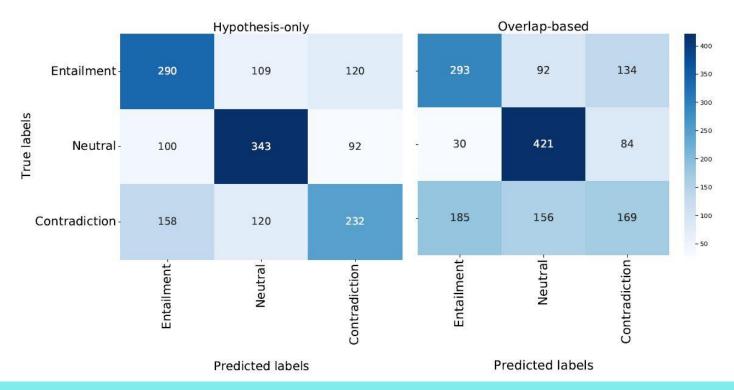
$$PMI(word, class) = \log \frac{p(word, class)}{p(word, .)p(., class)}.$$

	Word	Class	PMI	Counts
	never	Contradiction	0.852	6599/8363
	no	Contradiction	0.820	12499/16513
	nothing	Contradiction	0.775	2090/2758
MultiNLI	any	Contradiction	0.735	5430/7739
	none	Contradiction	0.681	553/702
Multiner	anything	Contradiction	0.668	2239/3336
	completely	Contradiction	0.664	855/1190
	also	Neutral	0.644	1845/2726
	refused	Contradiction	0.644	401/498
	nobody	Contradiction	0.603	612/881
	to	Neutral	0.488	3541/5266
	have	Neutral	0.481	845/1155
	the	Neutral	0.479	14194/21758
	definite	Entailment	0.478	144/146
SciTail	because	Neutral	0.466	571/749
SCITAII	system	Neutral	0.461	654/885
	68	Neutral	0.454	14790/23261
	a	Neutral	0.451	6086/9514
	off	Neutral	0.437	7644/12162
	and	Neutral	0.430	2771/4352
	(2	Neutral	0.244	95/158
	3H 2	Entailment	0.227	466/1053
	n	Contradiction	0.222	463/1053
	(only) تنها	Contradiction	0.221	61/87
Dans Tail	(be) باشد	Contradiction	0.202	202/440
FarsTail	(also) نیز	Neutral	0.179	50/76
	(only) فقط	Contradiction	0.168	38/50
	(self) خود	Neutral	0.163	143/319
	(after) بعد	Contradiction	0.162	74/144
	(work,effect) اثر	Entailment	0.159	70/135

Another approach for investigating dataset biases

- **1. Hypothesis-only model**: Fine-tuning the mBERT model on the hypotheses to predict the entailment labels without seeing the premises. The model obtained an accuracy of 55.31% on the test set.
- **2. Overlap-based model**: Using the cosine similarity between the bag-of-word count vectors of the premise and hypothesis as the input feature to investigate the ability of a model in deciding about the inference relationship just exploiting the similarity between the premise and hypothesis. An SVM classifier trained on this input feature obtained an accuracy of 56.46% on the test set.

Confusion matrices of the biased models



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Partitioning the test set into two subsets

We partitioned the FarsTail test set into two subsets (for each biased model): easy and hard.

% of the total data	Easy/Hard for each biased model			
32%	Easy for Hypothesis-only and Overlap-based biased models			
20%	Hard for Hypothesis-only and Overlap-based biased models			
25%	Hard for Hypothesis-only biased model			
23%	Hard for Overlap-based biased model			

Accuracy of different models on different subsets

	0	Hypothesis-only		Overlap-based	
\mathbf{Model}	Full	Easy	Hard	Easy	Hard
DecompAtt (word2vec)	0.6662	0.7341	0.5823	0.7633	0.5404
HBMP (word2vec)	0.6604	0.7618	0.5350	0.7565	0.5360
ESIM (fastText)	0.7116	0.7931	0.6109	0.8120	0.5815
mBERT	0.8338	0.8763	0.7811	0.8981	0.7504

These results shows that the models' accuracy on the hard subset obtained by the overlap-based biased model is usually lower than that of the hypothesis-only biased model. This reveals that the models exploit more of the overlap information between premises and hypotheses than the biased patterns in the hypotheses.

Conclusion

- We introduced, to the best of our knowledge, the first relatively large-scale NLI dataset for Persian language.
- We presented the details of the FarsTail development process, which is carefully designed to ensure the data quality.
- We also presented the dataset statistics as well as the results of some traditional and state-of-the-art methods on it. The best obtained result on the FarsTail test set, using the powerful BERT method, is 83.38%.
- We also investigated the dataset biases in FarsTail.

Thanks!

Any questions?

soroush.faridan@gmail.com faridan.github.io