Collecting Diverse Natural Language Inference Problems for Sentence Representation Evaluation

EMNLP 2018

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Collaborators















Premise: The brown cat ran

Hypothesis: The animal moved



Premise: The brown cat ran

Hypothesis: The animal moved

entailed



Premise: The brown cat ran

Multiple labeling schemas

Hypothesis: The animal moved

entailed



Premise: The brown cat ran

Multiple labeling schemas

Hypothesis: The animal moved

entailed not-entailed

entailment

neutral

contradiction



Premise: The brown cat ran

Hypothesis: The animal moved

entailed



Premise: The brown cat ran

Hypothesis: The animal moved





Premise: *The brown cat ran*

Hypothesis: *The animal moved*





Hypothesis: *The animal moved*

Premise: The brown cat ran





Why NLI as an NLP task?



Evaluation & Probing models







(Cooper et al., 1996)



FraCas: determine whether a model performs distinct types of reasoning

(Cooper et al., 1996)



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(Cooper et al., 1996)





(Dagan et al., 2006)



FraCas: determine whether a model performs distinct types of reasoning

(Cooper et al., 1996)

Pascal RTE: "a generic evaluation framework" to compare models

for distinct downstream tasks



(Dagan et al., 2006)





SNLI & Multi-NLI:

(Bowman et. al. 2015; Williams et. al. 2018)



<u>SNLI & Multi-NLI:</u> large scale datasets

(Bowman et. al. 2015; Williams et. al. 2018)



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Evaluate sentence representations

(Rep Eval 2017 Shared Task - Nangia et. al. 2017)



<u>SNLI & Multi-NLI:</u> large scale datasets

(Bowman et. al. 2015; Williams et. al. 2018)

Evaluate sentence representations

(Rep Eval 2017 Shared Task - Nangia et. al. 2017)

Training to improve models for downstream tasks

(Guo et. al. 2018)



Prior Dataset Characteristics



Prior Dataset Characteristics

NLU Insights



Prior Dataset Characteristics

NLU Insights

Generation Methods



Prior Dataset Characteristics

NLU Insights

Generation Methods

Small Probing Sets



Characteristic 1: NLU Insights

Understanding our models' reasoning capabilities?





Characteristic 1: NLU Insights

Jianpeng Cheng et al. '16	450D LSTMN with deep attention fusion	3.4m	88.5	86.3
Parikh et al. '16	200D decomposable attention model	380k	89.5	86.3
Parikh et al. '16	200D decomposable attention model with intra-sentence attention	580k	90.5	86.8
Munkhdalai & Yu '16b	300D Full tree matching NTI-SLSTM-LSTM w/ global attention	3.2m	88.5	87.3
Zhiguo Wang et al. '17	BIMPM	1.6m	90.9	87.5
Lei Sha et al. '16	300D re-read LSTM	2.0m	90.7	87.5
Yichen Gong et al. '17	448D Densely Interactive Inference Network (DIIN, code)	4.4m	91.2	88.0
McCann et al. '17	Biattentive Classification Network + CoVe + Char	22m	88.5	88.1
Chuanqi Tan et al. '18	150D Multiway Attention Network	14m	94.5	88.3
Xiaodong Liu et al. '18	Stochastic Answer Network	3.5m	93.3	88.5
Ghaeini et al. '18	450D DR-BiLSTM	7.5m	94.1	88.5
Yi Tay et al. '18	300D CAFE	4.7m	89.8	88.5
Qian Chen et al. '17	KIM	4.3m	94.1	88.6
Qian Chen et al. '16	600D ESIM + 300D Syntactic TreeLSTM (code)	7.7m	93.5	88.6
Peters et al. '18	ESIM + ELMo	8.0m	91.6	88.7
Boyuan Pan et al. '18	300D DMAN	9.2m	95.4	88.8
Zhiguo Wang et al. '17	BiMPM Ensemble	6.4m	93.2	88.8
Yichen Gong et al. '17	448D Densely Interactive Inference Network (DIIN, code) Ensemble	17m	92.3	88.9
Seonhoon Kim et al. '18	Densely-Connected Recurrent and Co-Attentive Network	6.7m	93.1	88.9
Zhuosheng Zhang et al. '18	SLRC	6.1m	89.1	89.1
Qian Chen et al. '17	KIM Ensemble	43m	93.6	89.1
Ghaeini et al. '18	450D DR-BiLSTM Ensemble	45m	94.8	89.3
Peters et al. '18	ESIM + ELMo Ensemble	40m	92.1	89.3
Yi Tay et al. '18	300D CAFE Ensemble	17.5m	92.5	89.3
Chuanqi Tan et al. '18	150D Multiway Attention Network Ensemble	58m	95.5	89.4
Boyuan Pan et al. '18	300D DMAN Ensemble	79m	96.1	89.6
Radford et al. '18	Fine-Tuned LM-Pretrained Transformer	85m	96.6	89.9
Seonhoon Kim et al. '18	Densely-Connected Recurrent and Co-Attentive Network Ensemble	53.3m	95.0	90.1





Expensive





Expensive



Leads to biases:



Expensive



Leads to biases:

Stereotypical

(Rudinger et. al. 2017)



Expensive



Leads to biases:

Stereotypical

(Rudinger et. al. 2017)

Class-based Statistical Irregularities

(Tsuchiya, 2018; Gururangan et al., 2018; Poliak et al., 2018)



Characteristic 3: Small Probing Sets



Characteristic 3: Small Probing Sets

FraCas is too small

Training neural network on 300 examples





Outline

- Introduction
- The DNC: Diverse NLI Collection
- Constructing the DNC
- Experiments & Results




Diverse Natural Language Inference Collection



Diverse Natural Language Inference Collection

Large scale collection of diverse NLI problems



Diverse Natural Language Inference Collection

Large scale collection of diverse NLI problems

Convert 7 semantic phenomena into NLI from 13 existing datasets



The DNC - Examples

	Event	Find him before he finds the dog food The finding did not happen	1
_	Factuality	 I'll need to ponder The pondering happened 	×
	Relation Extraction	 Ward joined Tom in their native Perth Ward was born in Perth Stefan had visited his son in Bulgaria 	
		 Stefan was born in Bulgaria ▶ Kim heard masks have no face value 	×
	Puns	 Kim heard a pun Tod heard that thrift is better than annuity Tod heard a pun 	×



Sem. Phenomena/Annotations	Dataset	# pairs	
Event Factuality	Decomp (Rudinger et al., 2018b) UW (Lee et al., 2015) MeanTime (Minard et al., 2016)	42K (41,888) 5K (5,094) .7K (738)	
Named Entity Recognition	Groningen (Bos et al., 2017) CoNLL (Tjong Kim Sang and De Meulder, 2003)	260K (261,406) 60K (59,970)	
Gendered Anaphora	Winogender (Rudinger et al., 2018a)	.4K (464)	
Lexicosyntactic Inference	VerbCorner (Hartshorne et al., 2013) MegaVeridicality (White and Rawlins, 2018) VerbNet (Schuler, 2005)	135K (138, 648) 11K (11,814) 2K (1, 950)	
Puns	(Yang et al., 2015) SemEval 2017 Task 7 (Miller et al., 2017)	9K (9,492) 8K (8,054)	
Relationship Extraction	FACC1 (Gabrilovich et al., 2013)	30K (30,920)	
Sentiment Analysis	(Kotzias et al., 2015)	6K (6,000)	
Combined	Diverse NLI Collection (DNC)	575K (576,438)	
	SNLI (Bowman et al., 2015) Multi-NLI (Williams et al., 2017)	570K 433K	



□ decompositional-semantics-initiative / DNC● Unwatch - 4★ Unstar9% Fork1									
<> Code	Issues 0	1) Pull requests 0	III Projects 0 III W	'iki 🔟 Insig	hts 🔅 Settin	gs			
Diverse Na types of rea	Diverse Natural Language Inference Collection - NLI dataset that can used to evaluate how well models perform distinct types of reasoning (EMNLP 2018) http://decomp.io/projects/diverse-nat								
natural-language-processing natural-language-ir		natural-language-inference	ence computational-semantics emnlp2018 Ma		Manage topics	Manage topics			
K	T 6 commits		₽ 1 branch		ase	se 👢 1 contributor			
Branch: mas	Branch: master New pull request Create new file Upload files Find file Clone or download								
azpoliał	azpoliak update README.md - inference is everything data Latest commit 6a8beee on Sep 14								
dev		Release	Released DNC and updated README			2 months ago			
i test			Released DNC and updated README			2 months ago			
🖬 train		Release	Released DNC and updated README			2 months ago			
README.md			update README.md - inference is everything data				a month ago		
additional_references.md			added bibs for original datasets				2 months ago		
inference_is_everything.zip			included White et al's IJCNLP 2017 recast data a montl			a month ago			

E README.md

DNC: Diverse Natural Language Inference Collection

Dataset associated and released as part of *Collecting Diverse Natural Language Inference Problems for Sentence Representation Evaluation* (EMNLP 2018).



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"Leverage existing semantic annotations to create NLI datasets that probe different semantic phenomena"



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Existing resources

"Leverage existing semantic annotations to create NLI datasets that probe different semantic phenomena"





"Leverage existing semantic annotations to create NLI datasets that probe different semantic phenomena"





Focused Evaluation Datasets that probe different semantic phenomena



Create natural language template



Create natural language template

Extract annotated preposition



Create natural language template

Extract annotated preposition

Fill in template with preposition



Create natural language template

Extract annotated preposition

Fill in template with preposition

Label example based on annotation



I enjoyed studying here





I enjoyed studying here

happened



I enjoyed studying here

The studying happened

entailed

not-entailed



I enjoyed studying here

The studying did not happen

entailed

not-entailed



I actually forgot to feed my chicken





I actually forgot to feed my chicken

did not happened



I actually forgot to feed my chicken

The feeding happened

entailed

not-entailed



I actually forgot to feed my chicken

The feeding did not happen

entailed

not-entailed



It Happened (White et. al. 2016; Rudinger et. al. 2018) 42K Examples



It Happened (White et. al. 2016; Rudinger et. al. 2018) 42K Examples

UW (Lee et. al. 2015) 5K Examples



It Happened (White et. al. 2016; Rudinger et. al. 2018) 42K Examples

UW (Lee et. al. 2015) 5K Examples

MeanTime (Minard et. al. 2016) 700 Examples



VerbNet Thematic Roles





floss-41.2.1

Members: 4, Frames: 4

MEMBERS			
BRUSH (FN 1; W FLOSS (FN 1; W SHAVE (FN 1; W WASH (FN 1; W	VN 3; G 1) N 1) VN 2; G 1) N 2, 3; G 1)		
Roles			
 AGENT [+ANIMATE] PATIENT [+BODY_PART] INSTRUMENT 			
FRAMES			
NP V NP			
EXAMPLE SYNTAX SEMANTICS	"The hygienist flossed my teeth." <u>AGENT V PATIENT</u> TAKE CAPE OF(DURING(E) ACENT PATIENT)		
NP V	TARE_OF(DORING(L), TOEN, TAILEN)		
EXAMPLE SYNTAX SEMANTICS	"I flossed." <u>Agent</u> V <u>TAKE_CARE_OF(DURING(E), Agent, ?Patient)</u>		

floss-41.2.1

Members: 4, Frames: 4

Members	
BRUSH (FN 1; W FLOSS (FN 1; W SHAVE (FN 1; W WASH (FN 1; W	(N 3; G 1) N 1) <u>1. Align tokens to Thematic Roles</u> (N 2; G 1) N 2, 3; G 1)
Roles	
 Agent [- Patient Instrum 	FANIMATE] [+BODY_PART] ENT
FRAMES	
NP V NP	
EXAMPLE SYNTAX	"The hygienist flossed my teeth." <u>AGENT V PATIENT</u>
SEMANTICS	TAKE_CARE_OF(DURING(E), AGENT, PATIENT)
NP V	
EXAMPLE	"I flossed."
SYNTAX	Agent V
SEMANTICS	TAKE_CARE_OF(DURING(E), AGENT, ?PATIENT)
SYNTAX SEMANTICS	AGENT V TAKE CARE OF(DURING(E), AGENT, ?PATIENT)
Members	
---	---
BRUSH (FN 1; W FLOSS (FN 1; W SHAVE (FN 1; W WASH (FN 1; W	(N 3; G 1) N 1) <u>1. Align tokens to Thematic Roles</u> (N 2; G 1) N 2, 3; G 1)
Roles	
 Agent [· Patient Instrum 	+ANIMATE] [+BODY_PART] ENT
FRAMES	
NP V NP	
EXAMPLE	"The hygienist flossed my teeth." hygienist Agent
SYNTAX	<u>Agent</u> V <u>Patient</u>
SEMANTICS	TAKE_CARE_OF(DURING(E), AGENT, PATIENT) Leeth Patient
NP V	
EXAMPLE	"I flossed."
SYNTAX	<u>Agent</u> V
SEMANTICS	TAKE_CARE_OF(DURING(E), AGENT, ?PATIENT)

Members	
BRUSH (FN 1; W FLOSS (FN 1; W SHAVE (FN 1; W WASH (FN 1; W	(N 3; G 1) N 1) <u>1. Align tokens to Thematic Roles</u> (N 2; G 1) N 2, 3; G 1)
Roles	
 Agent [- Patient Instrum 2, C 	FANIMATE] [+body_part] ENT Convert semantics into natural language templates
FRAMES	
NP V NP	
EXAMPLE	"The hygienist flossed my teeth."
SYNTAX	AGENT V PATIENT
SEMANTICS	TAKE_CARE_OF(DURING(E), AGENT, PATIENT)
NP V	
EXAMPLE	"I flossed."
SYNTAX	<u>Agent</u> V
SEMANTICS	TAKE_CARE_OF(DURING(E), AGENT, ?PATIENT)

MEMBERS	
BRUSH (FN 1; WI FLOSS (FN 1; WN SHAVE (FN 1; WN WASH (FN 1; WN	N 3; G 1) (1) <u>1. Align tokens to Thematic Roles</u> N 2; G 1) (2, 3; G 1)
Roles	
 Agent [+ Patient [Instrume 2, C 	ANIMATE] +body_part] NT Onvert semantics into natural language templates
FRAMES	
NP V NP	
EXAMPLE SYNTAX	"The hygienist flossed my teeth." Agent took care of <u>Patient</u> AGENT V PATIENT
SEMANTICS	TAKE_CARE_OF(DURING(E), AGENT, PATIENT)
NP V	
EXAMPLE	"I flossed."
SYNTAX	AGENT V
SEMANTICS	TAKE_CARE_OF(DURING(E), AGENT, ?PATIENT)

Members	
BRUSH (FN 1; W FLOSS (FN 1; W SHAVE (FN 1; W WASH (FN 1; W	(N 3; G 1) N 1) <u>1. Align tokens to Thematic Roles</u> (N 2; G 1) N 2, 3; G 1)
Roles	
 Agent [- Patient Instrum 2, C 	tanimate] [+body_part] Ent Convert semantics into natural language templates
FRAMES	
NP V NP	
EXAMPLE	"The hygienist flossed my teeth."
SYNTAX	<u>Agent</u> V <u>Patient</u>
SEMANTICS	TAKE_CARE_OF(DURING(E), AGENT, PATIENT)
NP V	3. Fill in natural language templates
EXAMPLE	"I flossed."
SYNTAX	<u>Agent</u> V
SEMANTICS	TAKE_CARE_OF(DURING(E), AGENT, ?PATIENT)

The hygienist flossed my teeth

Agent took care of Patient

entailed



The hygienist flossed my teeth

The hygienist took care of my teeth

entailed



The hygienist flossed my teeth

Patient took care of Agent

entailed



The hygienist flossed my teeth

My teeth took care of the hygienist

entailed



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- Introduction
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Experimental Goal



Experimental Goal

"demonstrate how the DNC can help to evaluate how well models capture different types of semantic reasoning necessary for general language understanding"























Results

Recast Data Model	NER	EF	RE	Puns	Sentiment	GAR	VC	MV	VN	
Majority (MAJ)	50.00	50.00	59.53	50.00	50.00	50.00	50.00	66.67	53.66	
No Pre-training										
InferSent	92.50	83.07	61.89	60.36	50.00	-	88.60	85.96	46.34	
Hyp-only	91.48	69.14	64.78	60.36	50.00	_	76.82	77.83	46.34	
Pre-trained DNC										
InferSent (update)	92.47	83.86	74.38	93.17	81.00	-	89.00	85.62	76.83	
InferSent (fixed)	92.20	81.07	74.11	87.76	77.33	50.65	88.59	83.84	67.68	
Hyp-only (update)	91.60	71.07	70.57	60.02	46.83	_	76.78	77.83	68.90	
Hyp-only (fixed)	91.37	69.74	65.97	56.44	48.17	50.00	76.78	77.83	59.15	
Pre-trained Multi-NLI										
InferSent (update)	92.37	83.03	76.08	92.48	83.50	-	88.45	85.11	78.05	
InferSent (fixed)	52.99	54.88	66.75	56.04	56.50	50.65	45.33	55.92	45.73	
Hyp-only (update)	91.62	70.64	69.91	60.36	49.33	_	76.82	77.83	68.29	
Hyp-only (fixed)	52.55	66.33	52.96	60.59	50.00	50.43	41.31	46.28	48.78	





Train models on each DNC dataset











Train models on each DNC dataset

Pre-train models on all of DNC or Multi-NLI









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Train models on each DNC dataset

Pre-train models on all of DNC or Multi-NLI

Evaluate fixed models trained on all of DNC or Multi-NLI





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Summary





The DNC: Diverse NLI Collection





The DNC: Diverse NLI Collection

Convert 13 existing datasets into NLI covering 7 semantic phenomena



Summary

The DNC: Diverse NLI Collection

Convert 13 existing datasets into NLI covering 7 semantic phenomena

Over half a million examples



Summary

The DNC: Diverse NLI Collection

Convert 13 existing datasets into NLI covering 7 semantic phenomena

Over half a million examples

Presented use case of DNC




Dataset creators:



Dataset creators: convert your data into NLI



Dataset creators: convert your data into NLI included in future DNC releases



Dataset creators: convert your data into NLI included in future DNC releases

Model creators:



Dataset creators:

convert your data into NLI included in future DNC releases

Model creators:

test your models ability to capture diverse types of reasoning



On the Evaluation of Semantic Phenomena in NMT Using NLI







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Branch: master - DNC / dev /		Create new file	Upload files	Find file	History
azpoliak Released DNC and updated README		Latest commit 399c4f7 on Aug 31			
recast_factuality_data.json	Released DNC and updated README			2 mon	ths ago
recast_factuality_metadata.json	Released DNC and updated README			2 mon	ths ago
recast_kg_relations_data.json	Released DNC and updated README			2 mon	ths ago
recast_megaveridicality_data.json	Released DNC and updated README			2 mon	ths ago
recast_megaveridicality_metadata.json	Released DNC and updated README			2 mon	ths ago
recast_ner_data.json	Released DNC and updated README			2 mon	ths ago
recast_ner_metadata.json	Released DNC and updated README			2 mon	ths ago
recast_puns_data.json	Released DNC and updated README			2 mon	ths ago
recast_puns_metadata.json	Released DNC and updated README			2 mon	ths ago
recast_sentiment_data.json	Released DNC and updated README			2 mon	ths ago
recast_sentiment_metadata.json	Released DNC and updated README			2 mon	ths ago
recast_verbcorner_data.json	Released DNC and updated README			2 mon	ths ago
recast_verbcorner_metadata.json	Released DNC and updated README			2 mon	ths ago
recast_verbnet_data.json	Released DNC and updated README			2 mon	ths ago
recast_verbnet_metadata.json	Released DNC and updated README			2 mon	ths ago



Data Example

```
"binary-label": false,
    "context": "The hygienist flossed my teeth .",
    "hypothesis": "My teeth took care of the hygienist .",
    "label": "not-entailed",
    "label-set": [
        "entailed",
        "not-entailed"
    ],
    "pair-id": 504820,
    "split": "dev",
    "type-of-inference": "Thematic Roles"
},
```



ł

MetaData Example

```
"corpus": "VerbNet",
"corpus-license": "http://verbs.colorado.edu/verbn
"corpus-sent-id": "floss-41.2.1_NP V NP",
"creation-approach": "automatic",
"misc": {
    "descriptionNumber": "0.2",
    "secondary": "Transitive",
    "xtag":
"pair-id": 504820
```



{

},

Structure of json files:

Data files:

Each datafile has the following keys and values:

- context : The context sentence for the NLI pair. The context is already tokenized.
- hypothesis : The hypothesis sentence for the NLI pair. The hypothesis is already tokenized.
- label : The label for the NLI pair
- label-set : The set of possible labels for the specific NLI pair
- binary-label : A True or False label. See the paper for details on how we convert the label into a binary label.
- split: This can be train, dev, or test.
- type-of-inference : A string indicating what type of inference is tested in this example.
- pair-id: A unique integer id for the NLI pair. The pair-id is used to find the corresponding metadata for any given NLI pair

[™] Metadata files:

- pair-id : A unique integer id for the NLI pair.
- corpus : The original corpus where this example came from.
- corpus-sent-id : The id of the sentence (or example) in the original dataset that we recast.
- corpus-license : The license for the data from the original dataset.
- creation-approach : Determines the method used to recast this example. Options are automatic , manual , or human-labeled.
- misc : A dictionary of other relevant information. This is an optional field.

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Thank you!















Data and paper available



