A Natural Proof System for Natural Language

NPS4NL-1: Natural Language Inference

Lasha Abzianidze Reinhard Muskens

university of groningen

Tilburg University

ESSLLI 2019 in Rīga, Latvija

About us

Lasha Abzianidze
University of Groningen

Reinhard Muskens
Tilburg University

Course is about

The following research questions are at the heart of the course:

- How are the meanings of natural language sentences related to each other?
- How to systematically reason with natural language sentences?
- How to get an explainable reasoning system?
- Can I use expressive but at the same time *friendly* meaning representations?

There will be many *natural* trees

Course is NOT about

- Machine leaning (and Artificial Neural Networks)
- Lexicalized formal compositional semantics:
  $[[\text{John}]]@([[\text{loves}]]@[[\text{Mary}]]) = \texttt{love(john,mary)}$
- Only toy examples
- Proving theorems about formal logics
  (but proving natural language theorems)

A few prerequisites

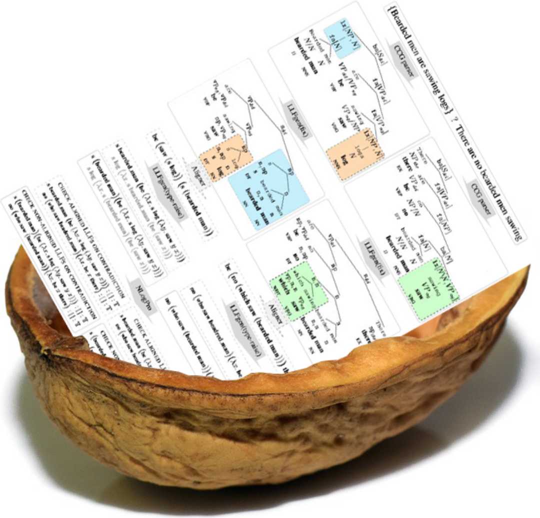
- Syntax of first-order logic formulas
- Understanding semantics of first-order logic formulas:
  $\exists y \forall x.\mathtt{love}(x, y) \rightarrow \forall x \exists y.\mathtt{love}(x, y)$
- Some knowledge of λ-calculus
- Some knowledge of simply typed λ-calculus

Outcome of the course

In the end of the course you will know about:

- Challenges posed by Natural Language Inference
- Pros & Cons of logic-based methods wrt NLI
- Nitty-gritty details of theorem proving with a tableau system
- Doing semantics with higher-order logic
- How to account for a semantic phenomena in Natural Tableau
- How to use the Natural Tableau prover to solving inference problems

Course in a nutshell



Topics per day

Mon Natural Language Inference
The task of NLI, monotonicity reasoning & natural logic (pros & cons)

Tue Semantic Tableau Method
Tableau systems for Propositional, First- and Higher-Order Logics

Wed Natural Tableau System
Lambda Logical Forms, Natural Tableau & tableau rules (part 1)

Thu Wide-Coverage Theorem Prover for Natural Language
Producing logical forms from syntactic trees, tableau rules (part 2)

Fri Natural Language Inference with Natural Theorem Prover
Solving problems from NLI datasets, evaluation and analysis

Course web page: naturallogic.pro/Teaching/esslli19/

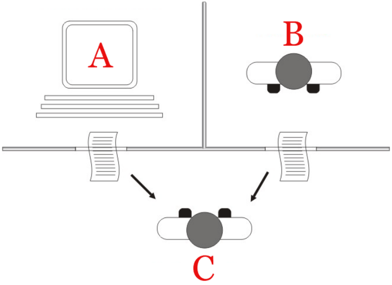
Natural Language Understanding

Natural language understanding is one of the main problems of AI and NLP.

How to test whether a machine/program understands a natural language?

estimate semantic competence in a natural language

Use the Turing test. ⚠ Too expensive! 👎 👎 👎



Juan Alberto Sánchez Margallo: https://commons.wikimedia.org/wiki/File:Test_de_Turing.jpg

Natural Language Understanding

Natural language understanding is one of the main problems of AI and NLP.

How to test whether a machine/program understands a natural language?

estimate semantic competence in a natural language

Given a sentence, ask what does it mean/tell.

A brown cat is lying on a mat

A1: A pet, which is brown, is lying

A2: A cat is on a mat

A3: There is an animal sleeping on a mat

⋮

⚠Evaluation of the answers requires a system that understands natural language. 👎👎

Natural Language Understanding

Natural language understanding is one of the main problems of AI and NLP.

How to test whether a machine/program understands a natural language?

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Given a sentence, ask a yes/no/dunno question about its meaning.
A brown cat is lying on a yellow mat

Q1: Is the brown cat lying on the mat? [Yes]
Q2: Is the mat soft? [Dunno]
Q3: Is the cat jumping on the mat? [No]

⋮

⚠This focuses on (long) questions and declarative sentences, and it is not straightforward to cover noun phrases and imperatives?

A cat on the mat   Feed the cat on the mat!

Natural Language Understanding

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Given two sentences $S1$ and $S2$, detect whether $S1$ entails $S2$.

$S1$: A brown cat is lying on a yellow mat

$S2$: There is an animal on a yellow-colored mat

Answer: Yes

$S1$: The cat lying on a mat

$S2$: The cat rolling on a yellow mat

Answer: No

Contrasting phrases of the same category, e.g., noun phrase, declarative sentences, questions, etc.

Recognizing Textual Entailment (2005-2013)

The task of Recognizing Textual Entailment (RTE) was introduced by [Dagan et al., 2005]:

- Textual entailment is defined as a *directional relationship* between pairs of text expressions, denoted by T (the entailing "Tex") and H (the entailed "Hypothesis"). We say that T entails H if humans reading T would typically infer that H is most likely true.
- An RTE task: given two texts, T (text) and H (hypothesis), detect textual entailment from T to H.
- The RTE1 to RTE3 challenges: binary classification
- The RTE4 to RTE8 challenges: 3-way classification with long texts

RTE problems

RTE2 GOLD: `non-entailment`

Drew Walker, NHS Tayside's public health director, said: "It is important to stress that this is not a confirmed case of rabies."

A case of rabies was confirmed

RTE2 GOLD: `entailment`

About two weeks before the trial started, I was in Shapiro's office in Century City

---

Shapiro works in Century City

RTE2 GOLD: `entailment`

The drugs that slow down or halt Alzheimer's disease work best the earlier you administer them

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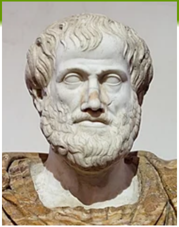
Alzheimer's disease is treated using drugs

Taken from [Dagan et al., 2013]

Long before RTE: Aristotle's syllogisms



Aristotle's syllogisms (4th century BC):

- 256 RTE problems
- Text consists of two sentences
- 24(!) of the problems are entailment

$\boxed{\text{OAO-3}}$ GOLD: `entailment`

Some cats have no tails
All cats are mammals

Some mammals have no tails

$\boxed{\text{IAE-3}}$ GOLD: `contradiction`

Some dogs have spots
All dogs are mammals

No mammals have spots

$\boxed{\text{IAA-1}}$ GOLD: `neutral`

Some vehicles are electric
All cars are vehicles

All cars are electric

$\boxed{\text{AAI-1}}$ GOLD: `neutral`

All canids are mammals
All cupacabras are canids

Some cupacabras are mammals

Just before RTE: FraCaS

The FraCaS test suite [Cooper et al., 1996]:

- 346 problems: a set of premises and a yes/no/dunno question
- Around half of the problems have multiple premises
- The problems are grouped based on the semantic phenomena: generalized quantifiers, plurals, ellipsis, adjectives, . . .

FraCaS-26 GOLD: yes

Most Europeans are resident in Europe
All Europeans are people
All people who are resident in Europe can travel freely within Europe

---

Can most Europeans travel freely within Europe?

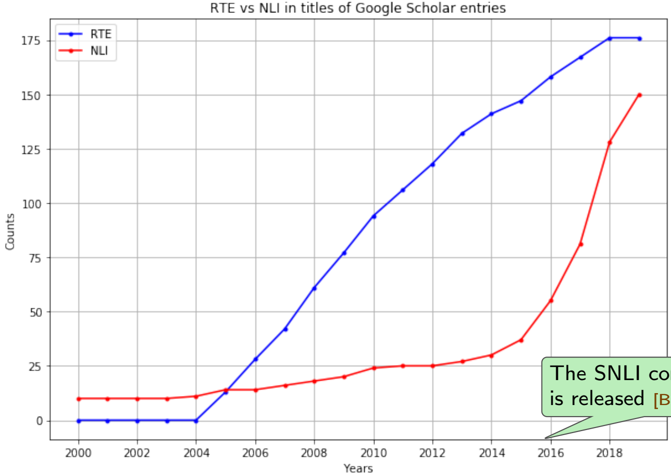
FraCaS-38 GOLD: unknown

No delegate finished the report.

Did any delegate finish the report on time?

After RTE: Natural Language Inference

Natural Language Inference is a recent term for Recognizing Textual Entailment.



The SNLI corpus for training ANNs is released [Bowman et al., 2015]

Modern NLI

The Stanford NLI (SNLI) corpus [Bowman et al., 2015]:

- Large corpus: 570K premise-hypothesis pairs
- Tackling entity & event co-reference by grounding in images
- Premises are image captions and hypotheses are generated by crowd workers
- Premise-hypothesis pairs are annotated by 5 crowd workers with 3 labels

The Multi-Genre NLI (MultiNLI) corpus [Williams et al., 2018]:

- Large corpus: 433K premise-hypothesis pairs
- It is modeled on the SNLI corpus
- 10 genres: Fiction, Governmnet, Slate, Telephone, Travel, 9/11,. . .
- Used as a sentence encoder benchmark at RepEval 2019

Examples from SNLI*

SNLI-3581451227.jpg#4r1c GOLD: `contradiction`[1c]

A little girl and boy after a wedding in a field

the sail boat sank in the ocean

SNLI-475816542.jpg#2r1c GOLD: `contradiction`[3c2e]

A black and a brown dog are running toward the camera.

A black and a brown cat are running toward the camera.

SNLI-4837051771.jpg#2r1n GOLD: `neutral`[2e3n]

A small ice cream stand with two people standing near it.

Two people in line to buy icecream.

SNLI-2218907190.jpg#1r1e GOLD: `entailment`[2c3e]

A dog begins to climb a brick staircase near plants.

A dog is going up the stairs.

*Arguable examples

Critical look at SNLI

In the test part of SNLI, 12.2% of problems get 2vs3 annotations.

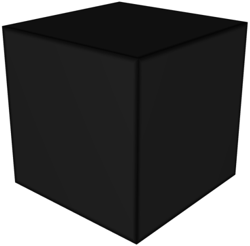
Annotation artifacts inflate systems' performance
[Poliak et al., 2018, Gururangan et al., 2018]:

- Hypothesis only baselines score strikingly high wrt the majority class baseline: 69.2% vs 33.8% accuracy
- *animal*, *outdoors*, and *person* often in `entailment` hypotheses
- *tall*, *sad*, and *first* often in `neutral` hypotheses
- *cat*, *sleeping*, and *no* often in `contradiction` hypotheses

Smart black boxes

Author performance on test-SNLI (91.4%) is already suppressed by a deep neural network-based system (91.6%) [Liu et al., 2019]

☞SNLI leaderboard



What does this mean?

Specially dedicated workshops:
BlackboxNLP 2018 and 2019

Harder challenges aka *Task-Independent Sentence Understanding*:

☞GLUE leaderboard

☞SuperGLUE leaderboard

Explainable reasoning

Explainable reasoning is a feature associated with a white box systems:

- Explain entailment by providing some sort of proof or argument
- Explain contradiction by highlighting the incompatible cases
- Explain neutral relation by providing counterexamples for entailment and contradiction

e-SNLI – NLI with natural language explanations [Camburu et al., 2018]:

- For each labelled NLI problem, crowd workers gave explanations;
- Also the word relevant for explanations were highlighted;
- An NLI system needs to predict a label and an explanation;
- How to evaluate predicted explanation automatically?
  BLEU-score is a poor metric for this purpose.

Examples from e-SNLI

SNLI-3581451227.jpg#4r1c GOLD: `contradiction`[1c]

A little **girl and boy** after a wedding **in a field**

the **sail boat** sank **in the ocean**

A girl and boy are people, not a thing, as a sail boat is. You cannot be in a field and in the ocean at the same time

SNLI-475816542.jpg#2r1c GOLD: `contradiction`[3c2e]

A black and a brown **dog** are running toward the camera.

A black and a brown **cat** are running toward the camera.

They refer to a dog, not a cat

The animal is either a cat or a dog

A dog cannot be a cat

Examples from e-SNLI (II)

SNLI-4837051771.jpg#2r1n   GOLD: `neutral`[2e3n]

A small ice cream stand with two people standing near it.

Two people in line to buy icecream.

Being near a stand doesn't mean you have to buy anything

Just because two people are standing near an ice cream stand, doesn't mean they are in line to buy ice cream

People who are standing near an ice cream stand are not always in line to buy ice cream

SNLI-2218907190.jpg#1r1e   GOLD: `entailment`[2c3e]

A dog begins to climb a brick staircase near plants.

A dog is going up the stairs.

Brick staircase is a paraphrase of stairs, and going up means to climb

Climbing implies going up

A DOG IS CLIMBING UP THE STAIRS

Shortcomings of NLI systems

- Few NLI systems are able to reason over multiple premises.
- Most NLI systems do not use logic-based reasoning: poor at processing Booleans (e.g., *or*, *not*) and quantifiers (e.g., *every*, *no*).

  P1: Most boxers have been knocked out
  P2: All boxers are athletes
  P3: All athletes who has been knocked out has a broken nose

  ---
  C: Most boxers have a broken nose
- SOTA NLI systems are not explanatory (though pretty good).
- Most RTE systems can be fooled easily (i.e. not having high precision)

  SICK-1745 GOLD:: `neutral`
  T: A man is pushing the buttons of a microwave

  H: A man is being pushed toward the buttons of a microwave

Shortcomings of logic-based NLI systems

- Their logic is often not expressive enough to model some aspects of linguistics semantics: higher-order terms like generalized quantifiers (e.g., *few*, *most*) and subsective modifiers e.g. *competent*, *slowly*.
- Translation of linguistic semantics into formal logic is usually a complex and immense problem, e.g., NL text into first-order logic [Bos, 2008].
- After the translation, information about constituency and syntax is not available in a formal language while the information is often crucial for *shallow* reasoning, e.g., monotonicity reasoning.

  SICK-8145 GOLD: `entailment`

  T: A woman in blue has a yellow ball in the mitt

  H: A woman in blue has a yellow ball in the hand

How logic can be natural?

Natural logic is a hypothetical logic which is built in natural language and represents its integral part.

It is a theory about "the regularities governing the notion of a valid argument for reasoning in natural language" [Lakoff, 1970].

"Natural logic is a somewhat loose [...] term for [...] attempts [...] at describing basic patterns of human reasoning directly in natural language without the intermediate of some formal system" [van Benthem, 2008].

Natural logic is "the study of inference in natural language, done as close as possible to the surface forms" [Moss, 2010b].

Monotonicity reasoning

The most popular and success story of natural logic is monotonicity reasoning.

Monotonicitity reasoning is about replacing phrases in a premise in such a way that the obtained sentences are entailment of the premise.

GOLD: `entailment`

P: Every man who consumed alcohol devoured most snacks

H: Every young man who drank beer ate some snacks

GOLD: `entailment`

P: $3 \times [s_3(x) = x + 3](2) \ \leq \ [p_3(x) = x^3]\big([m_4(x) = x \pmod 4](7)\big)$

H: $2 \times [s_1(x) = x + 1](1) \ \leq \ [p_4(x) = x^4]\big([m_8(x) = x \pmod 8](7)\big)$

Do you see similarity between these two entailment pairs?

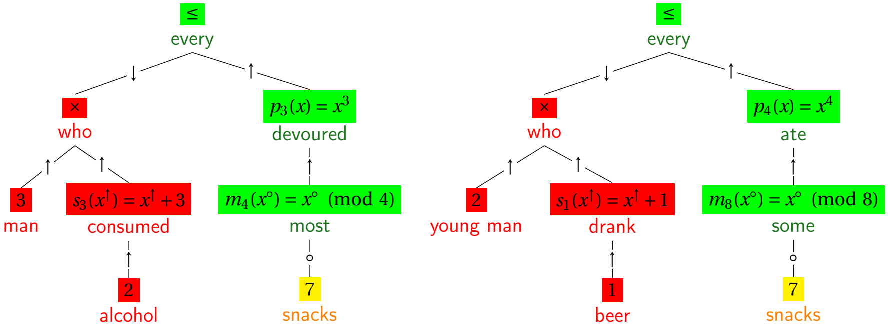
Now?

Monotonicity reasoning in action

GOLD: `entailment`

P: $3 \times [s_3(x) = x+3](2) \;\le\; [p_3(x) = x^3]\big([m_4(x) = x \pmod 4](7)\big)$

H: $2 \times [s_1(x) = x+1](1) \;\le\; [p_4(x) = x^4]\big([m_8(x) = x \pmod 8](7)\big)$



GOLD: `entailment`

P: Every man who consumed alcohol devoured most snacks

H: Every young man who drank beer ate some snacks

NatLog [MacCartney, 2009]

First NLI system that introduced natural logic to the NLP community

- Semantic relation over lexical items
- Union of the semantic relations
- Projection of the relations

symbol[10]	name	example	set theoretic definition[11]
$x \equiv y$	equivalence	*couch* $\equiv$ *sofa*	$x = y$
$x \sqsubset y$	forward entailment	*crow* $\sqsubset$ *bird*	$x \subset y$
$x \sqsupset y$	reverse entailment	*Asian* $\sqsupset$ *Thai*	$x \supset y$
$x \wedge y$	negation	*able* $\wedge$ *unable*	$x \cap y = \emptyset \wedge x \cup y = U$
$x \mid y$	alternation	*cat* $\mid$ *dog*	$x \cap y = \emptyset \wedge x \cup y \neq U$
$x \smile y$	cover	*animal* $\smile$ *non-ape*	$x \cap y \neq \emptyset \wedge x \cup y = U$
$x \# y$	independence	*hungry* # *hippo*	(all other cases)

NatLog [MacCartney, 2009]

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- Semantic relation over lexical items
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$\bowtie$	$\equiv$	$\sqsubset$	$\sqsupset$	$\wedge$	$\mid$	$\smile$	$\#$
$\equiv$	$\equiv$	$\sqsubset$	$\sqsupset$	$\wedge$	$\mid$	$\smile$	$\#$
$\sqsubset$	$\sqsubset$	$\sqsubset$	$\equiv\sqsubset\sqsupset\mid\#$	$\mid$	$\mid$	$\sqsubset\wedge\mid\smile\#$	$\sqsubset\mid\#$
$\sqsupset$	$\sqsupset$	$\equiv\sqsubset\sqsupset\smile\#$	$\sqsupset$	$\smile$	$\sqsupset\wedge\mid\smile\#$	$\smile$	$\sqsupset\smile\#$
$\wedge$	$\wedge$	$\smile$	$\mid$	$\equiv$	$\sqsupset$	$\sqsubset$	$\#$
$\mid$	$\mid$	$\sqsubset\wedge\mid\smile\#$	$\mid$	$\sqsubset$	$\equiv\sqsubset\sqsupset\mid\#$	$\sqsubset$	$\sqsubset\mid\#$
$\smile$	$\smile$	$\smile$	$\sqsupset\wedge\mid\smile\#$	$\sqsupset$	$\sqsupset$	$\equiv\sqsubset\sqsupset\smile\#$	$\sqsupset\smile\#$
$\#$	$\#$	$\sqsubset\smile\#$	$\sqsupset\mid\#$	$\#$	$\sqsupset\mid\#$	$\sqsubset\smile\#$	$\equiv\sqsubset\sqsupset\wedge\mid\smile\#$

NatLog [MacCartney, 2009]

First NLI system that introduced natural logic to the NLP community

- Semantic relation over lexical items
- Union of the semantic relations
- Projection of the relations

	projectivity for 1st argument							projectivity for 2nd argument						
quantifier	$\equiv$	$\sqsubset$	$\sqsupset$	$\wedge$	$\mid$	$\smile$	#	$\equiv$	$\sqsubset$	$\sqsupset$	$\wedge$	$\mid$	$\smile$	#
some	$\equiv$	$\sqsubset$	$\sqsupset$	$\smile^{\dagger}$	#	$\smile^{\dagger}$	#	$\equiv$	$\sqsubset$	$\sqsupset$	$\smile^{\dagger}$	#	$\smile^{\dagger}$	#
no	$\equiv$	$\sqsupset$	$\sqsubset$	$\mid^{\dagger}$	#	$\mid^{\dagger}$	#	$\equiv$	$\sqsupset$	$\sqsubset$	$\mid^{\dagger}$	#	$\mid^{\dagger}$	#
every	$\equiv$	$\sqsupset$	$\sqsubset$	$\mid^{\ddagger}$	#	$\mid^{\ddagger}$	#	$\equiv$	$\sqsubset$	$\sqsupset$	$\mid^{\dagger}$	$\mid^{\dagger}$	#	#
not every	$\equiv$	$\sqsubset$	$\sqsupset$	$\smile^{\ddagger}$	#	$\smile^{\ddagger}$	#	$\equiv$	$\sqsupset$	$\sqsubset$	$\smile^{\dagger}$	$\smile^{\dagger}$	#	#
at least two	$\equiv$	$\sqsubset$	$\sqsupset$	#	#	#	#	$\equiv$	$\sqsubset$	$\sqsupset$	#	#	#	#
most	$\equiv$	#	#	#	#	#	#	$\equiv$	$\sqsubset$	$\sqsupset$	$\mid$	$\mid$	#	#
exactly one	$\equiv$	#	#	#	#	#	#	$\equiv$	#	#	#	#	#	#
all but one	$\equiv$	#	#	#	#	#	#	$\equiv$	#	#	#	#	#	#

NatLog in action

P: John refused to move without blue jeans

H: John didn't dance without pants

Detect polarities of the words in the premise

	Sentence & Atomic edit	Lexical	Projected	Overall
(S0)	John refused to move without blue jeans			
	(E1) del(refused to)	$\mid$	$\mid$	$\mid$
(S1)	John moved without blue jeans			
	(E2) ins(didn't)	$^\wedge$	$^\wedge$	$\sqsubset$
(S2)	John didn't moved without blue jeans			
	(E3) sub(move, dance)	$\sqsupset$	$\sqsubset$	$\sqsubset$
(S3)	John didn't dance without blue jeans			
	(E4) del(blue)	$\sqsubset$	$\sqsubset$	$\sqsubset$
(S4)	John didn't dance without jeans			
	(E5) sub(jeans, pants)	$\sqsubset$	$\sqsubset$	$\sqsubset$
(S5)	John didn't dance without pants			

$$S0 \mid S1 \bowtie S1 {}^\wedge S2 \bowtie S2 \sqsubset S3 \bowtie S3 \sqsubset S4 \bowtie S4 \sqsubset S5 = S0 \sqsubset S5$$

Shortcomings of NatLog

- Cannot account for paraphrases:

  John bought a car from Bill
  Bill sold a car to John

  A student wrote an essay
  An essay was written by a student

- *Weaker* than first-order logic:

  Not all bird fly
  Some birds does not fly

- The word-alignment and -substitution nature of reasoning falls short of processing multiple premises

Related work

Other works on monotonicity reasoning and natural logic:

- First study of monotonicity reasoning as a formal calculus [Van Benthem, 1986, van Benthem, 1987, Sánchez-Valencia, 1991]
- Moving from syllogistic logics towards natural logic [Moss, 2010a]
- A tableau proof system for a fragment of natural logic [Muskens, 2010]
- Formal system for extended monotonicity reasoning [MacCartney and Manning, 2008, Icard, 2012, Icard and Moss, 2014]

Working systems:

- Monotonicity-based inference system for a fragment of English, operating on categorical grammar derivation trees [Fyodorov et al., 2003, Zamansky et al., 2006]
- Implementation of syllogistic logic with monotonicity [Eijck, 2005]
- Two implementations of extended syllogistic logics [Hemann et al., 2015]
- Natural language inference using polarity-marked parse trees [Hu et al., 2019]

Conclusion

The RTE/NLI task can be seen "as the best way of testing an NLP system's semantic capacity" [Cooper et al., 1996].

The NLI task is popular: many benchmarks and datasets

NLI systems comes with many flavours but we focus on logic-based ones

Monotonicity reasoning, the signature of natural logic

- Polarity marking
- String edit and word replacement reasoning

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