

# Natural Language Inference in the Real World

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# Natural Language Inference

# Natural Language Inference

A man is pointing at a silver sedan.

# Natural Language Inference

A man is pointing at a silver sedan.

There is no man pointing at a car.



# Natural Language Inference

A man is pointing at a silver **sedan**.

There is no man pointing at a **car**.

# Natural Language Inference

A man is pointing at a **silver** **sedan**.

There is no man pointing at a **car**.

# Natural Language Inference

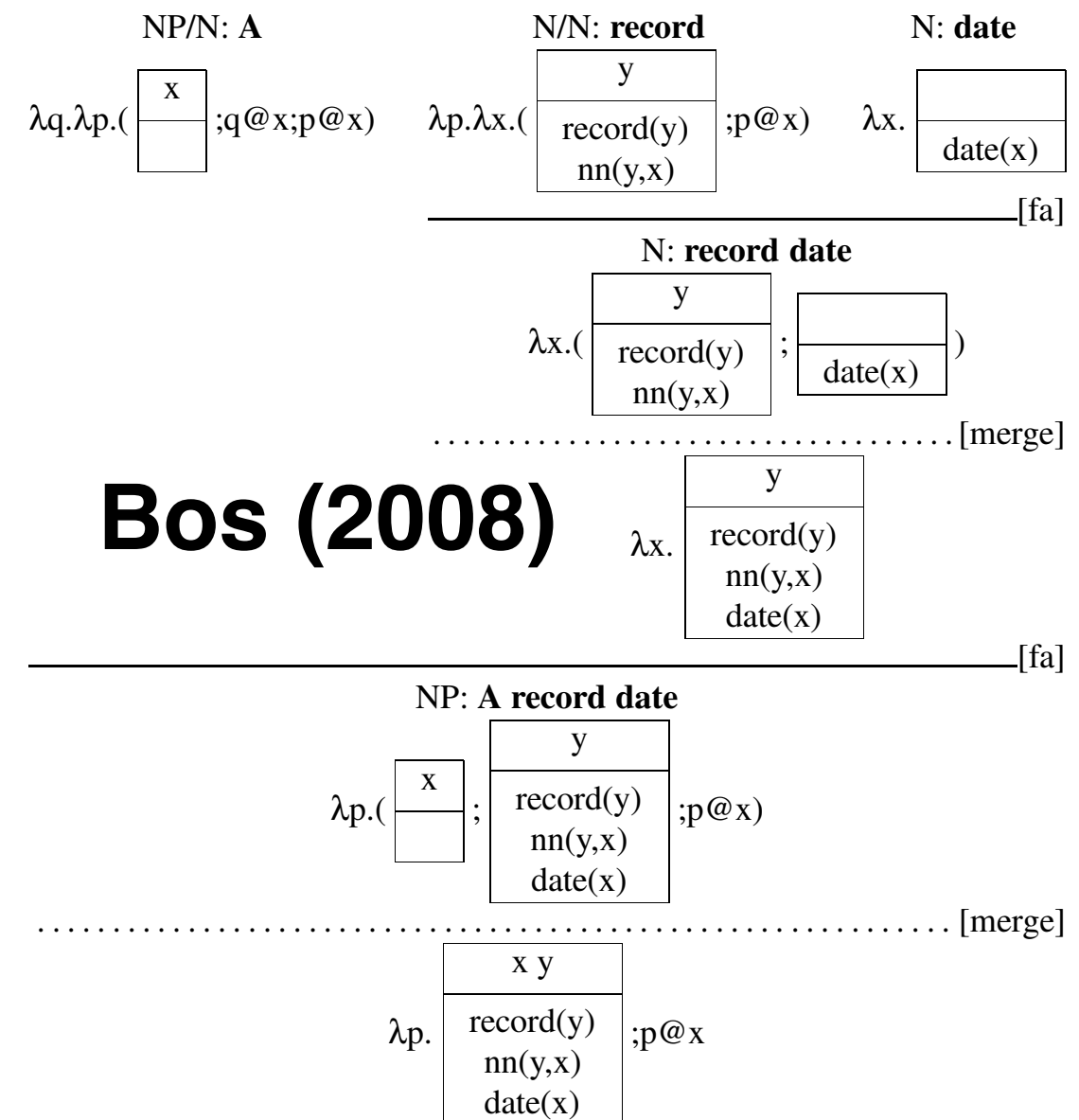
A man is pointing at a **silver** **sedan**.

There is **no** man pointing at a **car**.

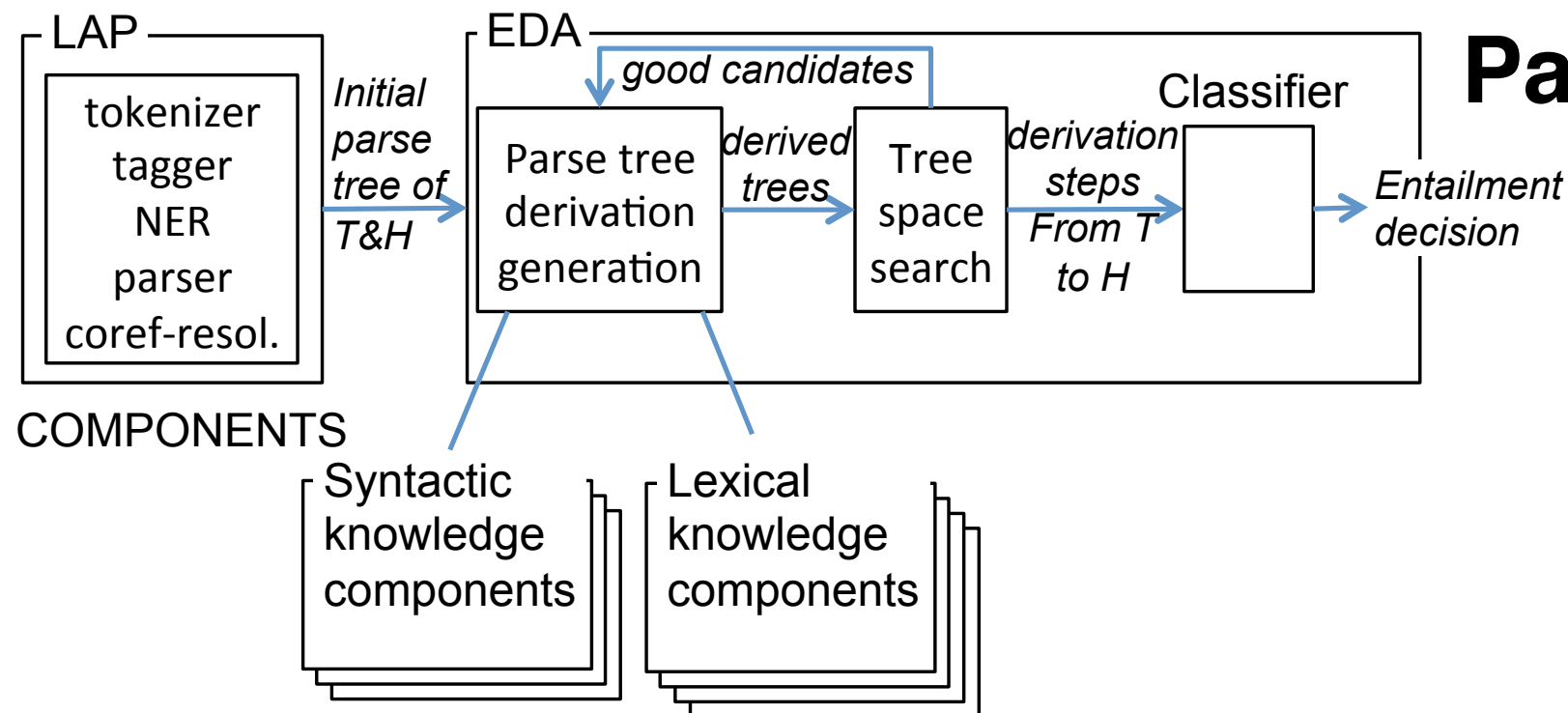
# Natural Language Inference

A man is pointing at a

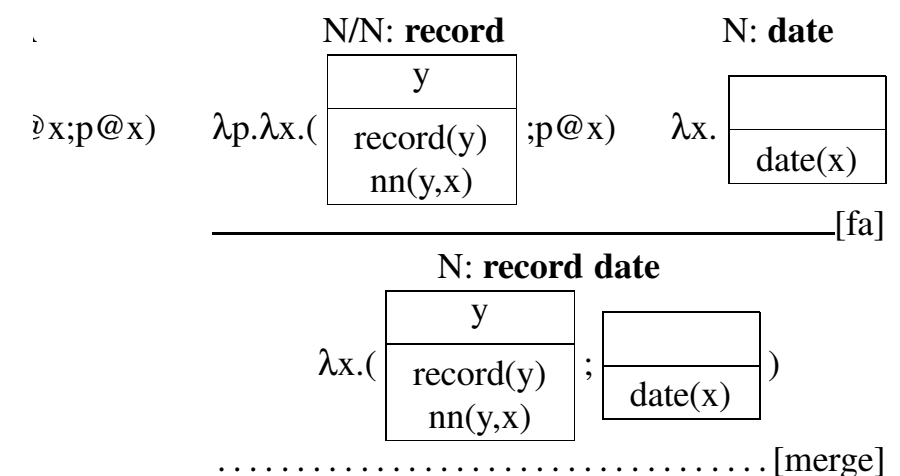
There is **no** man pair



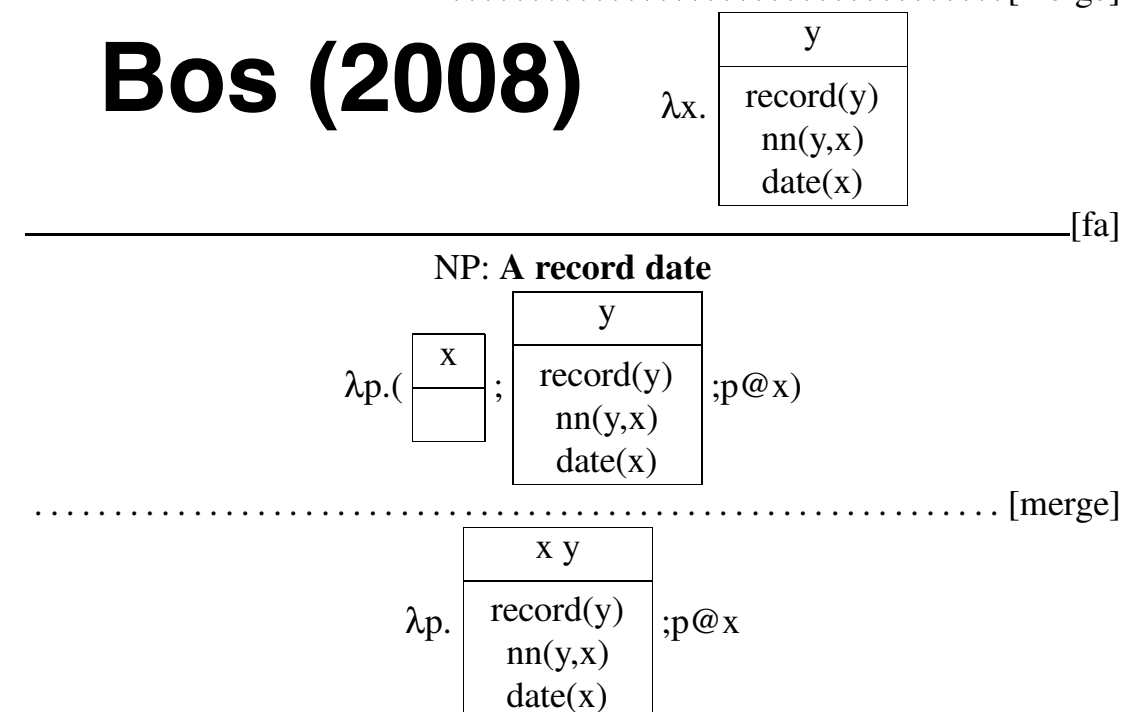
# Natural Language Inference



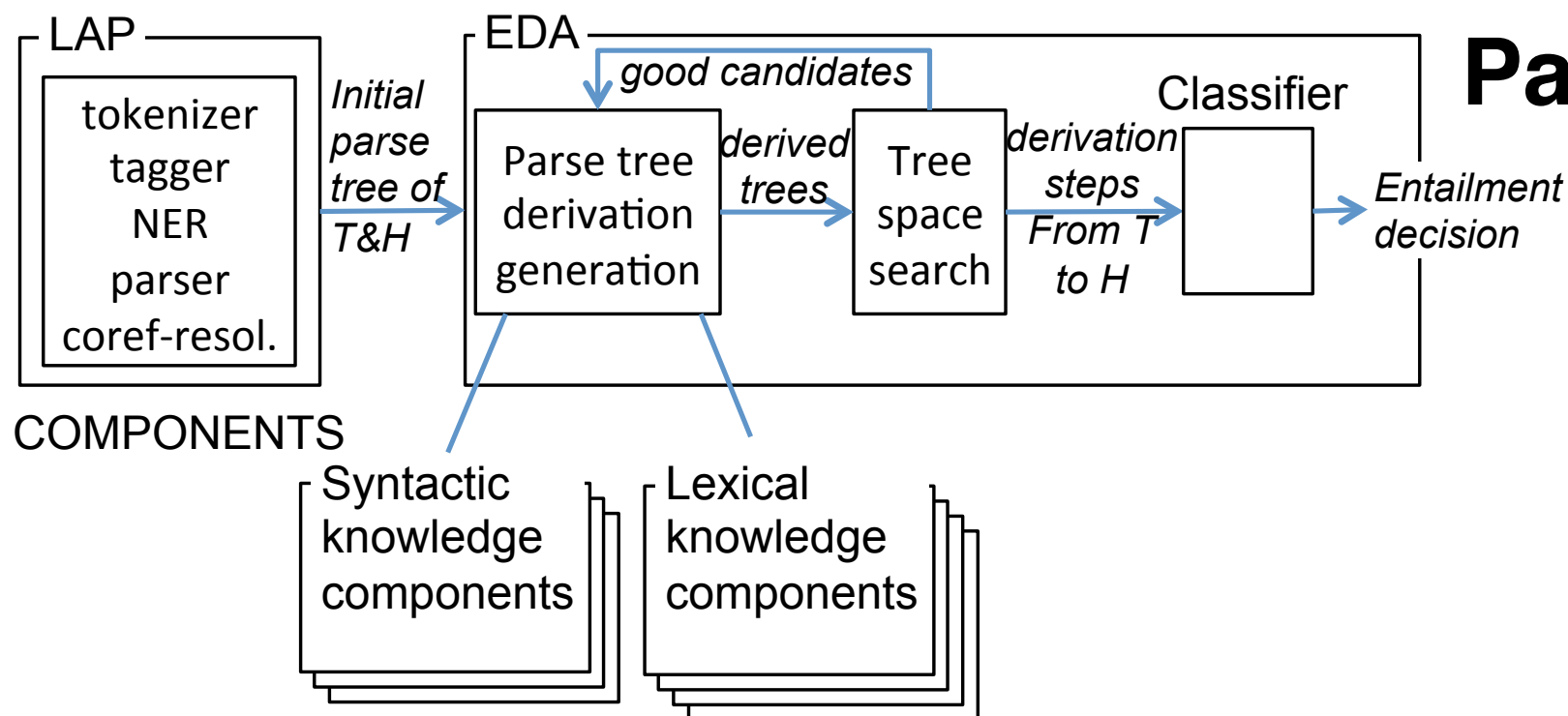
**Padó et al. (2015)**



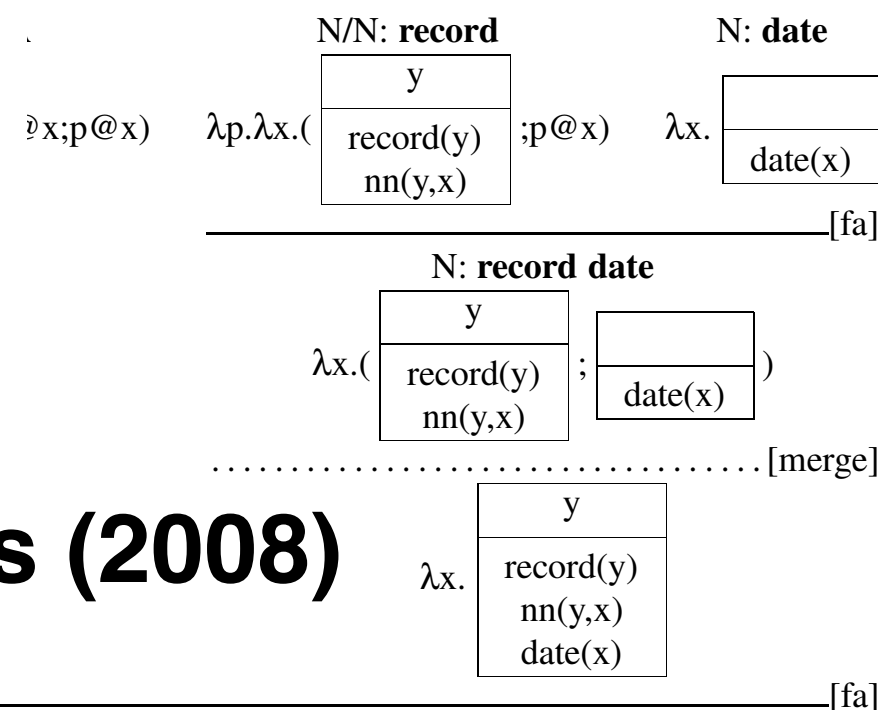
**Bos (2008)**



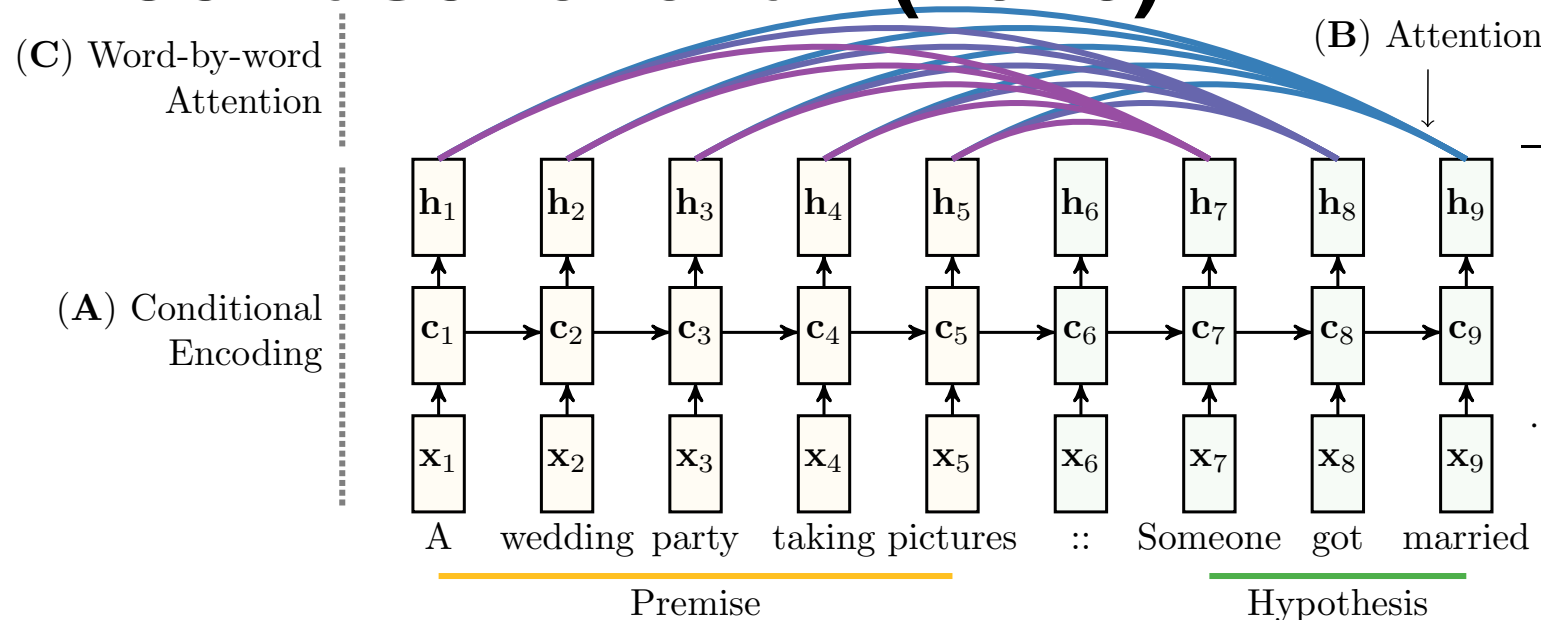
# Natural Language Inference



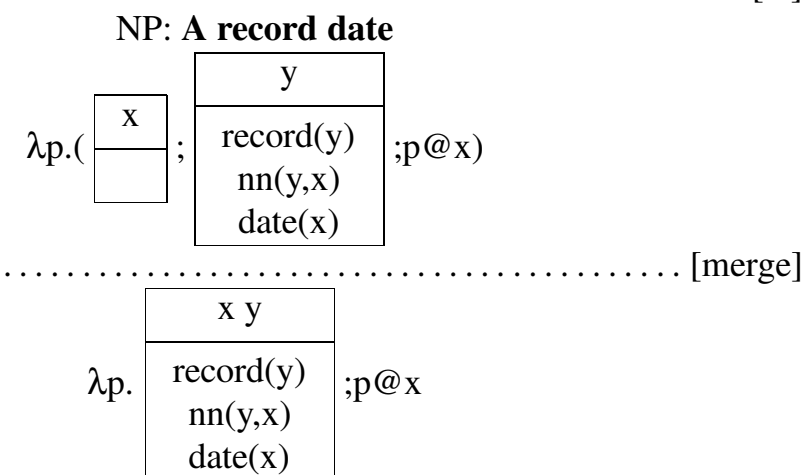
**Padó et al. (2015)**



**Rocktäschel et al. (2016)**



**Bos (2008)**



# Natural Language Inference

A man is pointing at a silver sedan.

No man is pointing at a car.

# Natural Language Inference

A man is pointing at a silver sedan.

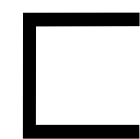
No man is pointing at a car.



# Natural Language Inference

A man is pointing at a silver **sedan**.

A man is pointing at a silver **car**. SUB(**sedan**, **car**)



yes

No man is pointing at a car.

# Natural Language Inference

A man is pointing at a silver sedan.

A man is pointing at a **silver** car. SUB(sedan, car)

☒ yes

A man is pointing at a car.

DEL(**silver**)

☒ yes

No man is pointing at a car.

# Natural Language Inference

A man is pointing at a silver sedan.

A man is pointing at a silver car. SUB(sedan, car)  yes

A man is pointing at a car. DEL(silver)  yes

**No** man is pointing at a car. INS(**no**)  no

# Natural Language Inference

A man is pointing at a silver sedan.

# Natural Language Inference

A man is pointing at a silver sedan.

Jimmy Dean refused to dance without pants.

# Natural Language Inference

A man is pointing at a silver sedan.

Last December they had argued that the council  
had failed to consider possible environmental  
effects of contaminated land at the site.

# Natural Language Inference

A man is **pointing** at a **silver sedan**.

Last December they had argued that the council had failed to consider possible environmental effects of contaminated land at the site.

# Natural Language Inference

A man is **pointing** at a **silver sedan**.

Last December they had **argued that** the council had **failed to consider possible environmental effects** of contaminated land at the site.



# Natural Language Inference

## Question Answering

Last December they had argued that **the council had failed to consider possible environmental effects** of contaminated land at the site.

Did the council **consider** the **environmental effects**?

Yes/No

# Natural Language Inference

## Summarization

Last December they had argued that **the council had failed to consider possible environmental effects** of contaminated land at the site.

They argued that the council **didn't consider environmental effects.**

# Natural Language Inference

Dialogue

**I decided I don't want to go to** that **party** on Saturday.

Remove from calendar?

# Wish List

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- We want to **get out of the “lab”** and model language that people actually use

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- We want rules for logical composition that are **descriptive rather than prescriptive** based on judgements by **real people**

# Wish List

- We want to **get out of the “lab”** and model language that people actually use
- We want rules for logical composition that are **descriptive rather than prescriptive** based on judgements by **real people**
- We want methods that are **derived from data**, rather than reliant on lexicons or ontologies

Last December they had argued that the council had failed to consider possible effects of contaminated land at the site.

The council considered environmental consequences.



Last December they had argued that the council had failed to consider possible effects of contaminated land at the site.

The council considered environmental consequences.

SUB(**effects, consequences**)

Last December they had argued that the council had failed to consider possible **effects** of contaminated land at the site.

The council considered environmental **consequences**.

**lexical semantics**

# INS(**environmental**)

Last December they had argued that the council had failed to consider possible effects of contaminated land at the site.

The council considered **environmental** consequences.

## **modifiers**

# DEL(**possible**)

Last December they had argued that the council had failed to consider **possible** effects of contaminated land at the site.

The council considered **environmental** consequences.

## **(non-subsective) modifiers**

# SUB(**consider**, **consider**)

Last December they had argued that the council had failed to **consider** possible effects of contaminated land at the site.

The council **considered** environmental consequences.

## **predicates**

# DEL(**fail to**)

Last December they had argued that the council had **failed to** consider possible effects of contaminated land at the site.

The council considered environmental consequences.

**“higher order”  
predicates**

SUB(**effects, consequences**)

Last December they had argued that the council had failed to consider possible **effects** of contaminated land at the site.

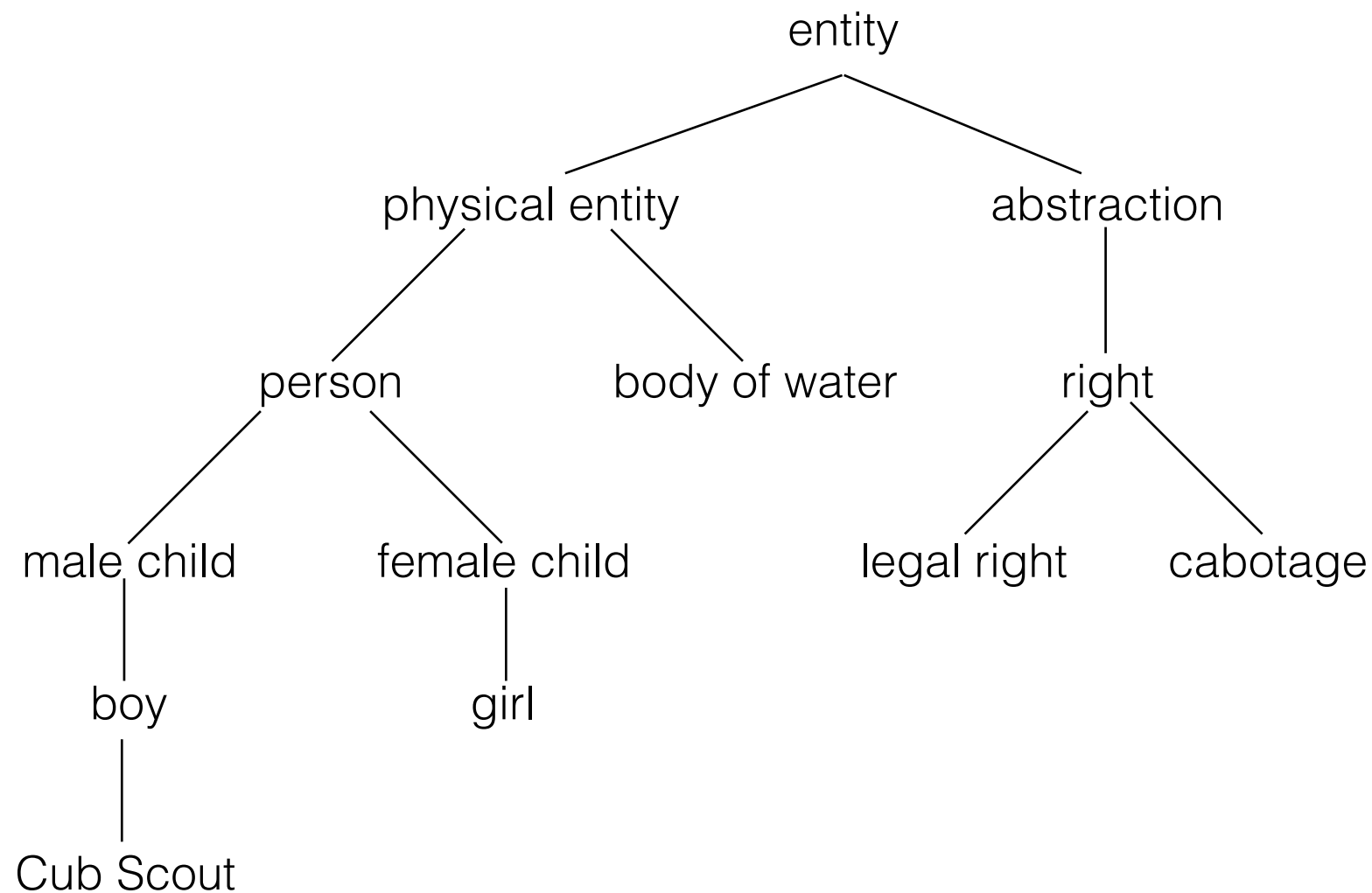
The council considered environmental **consequences**.

**lexical semantics**

# Lexical Semantics

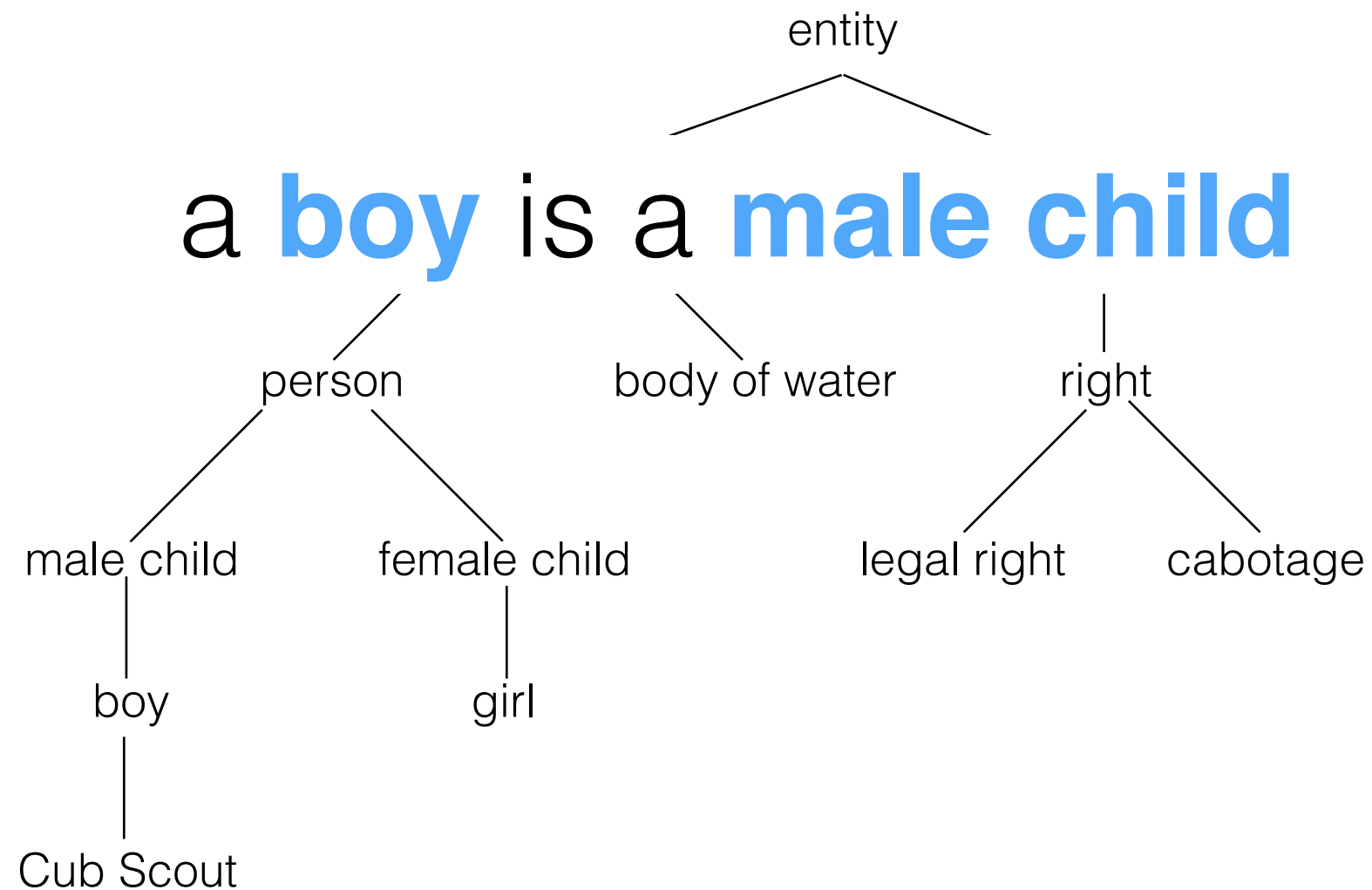


# Lexical Semantics



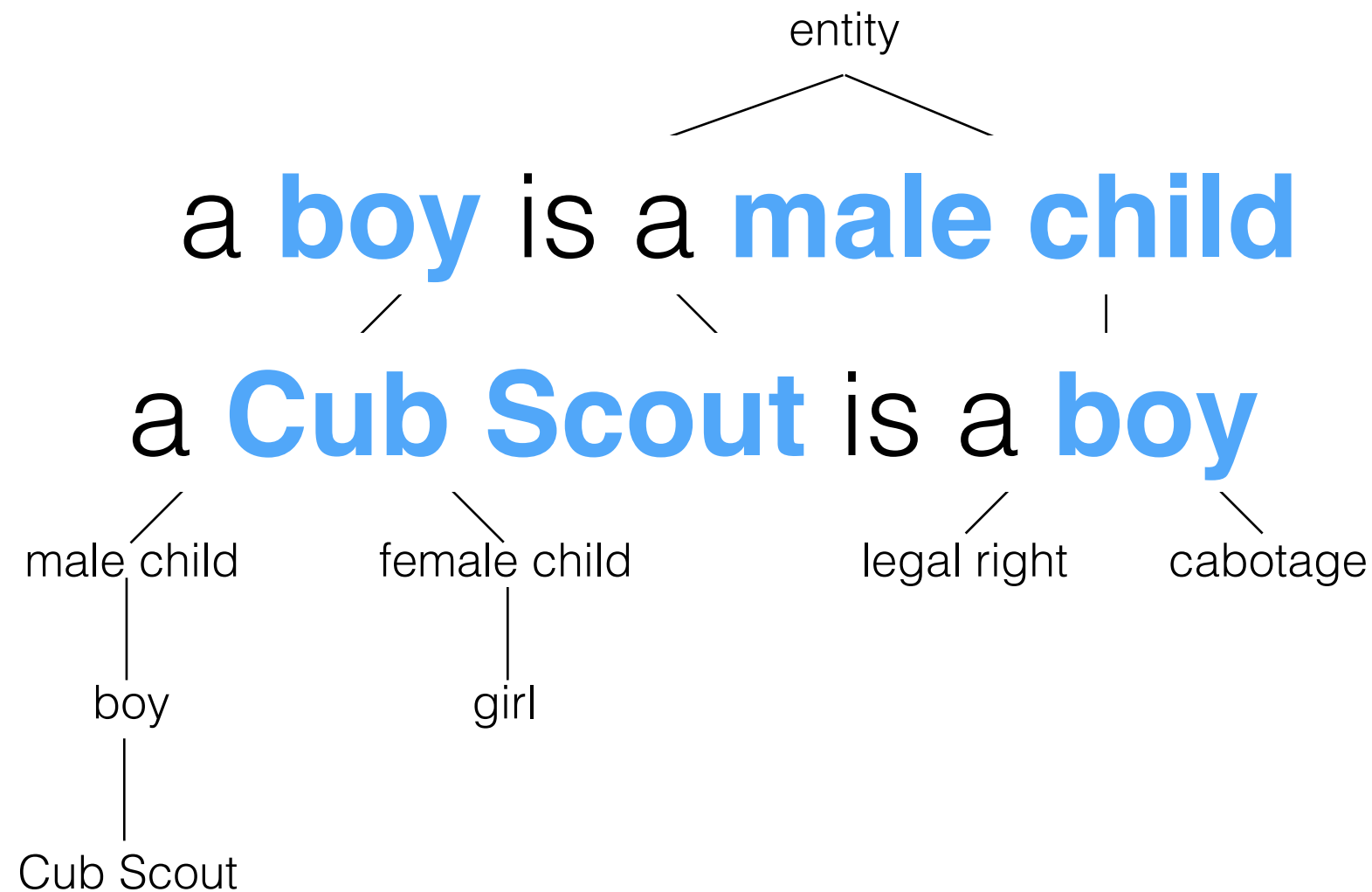
WordNet

# Lexical Semantics



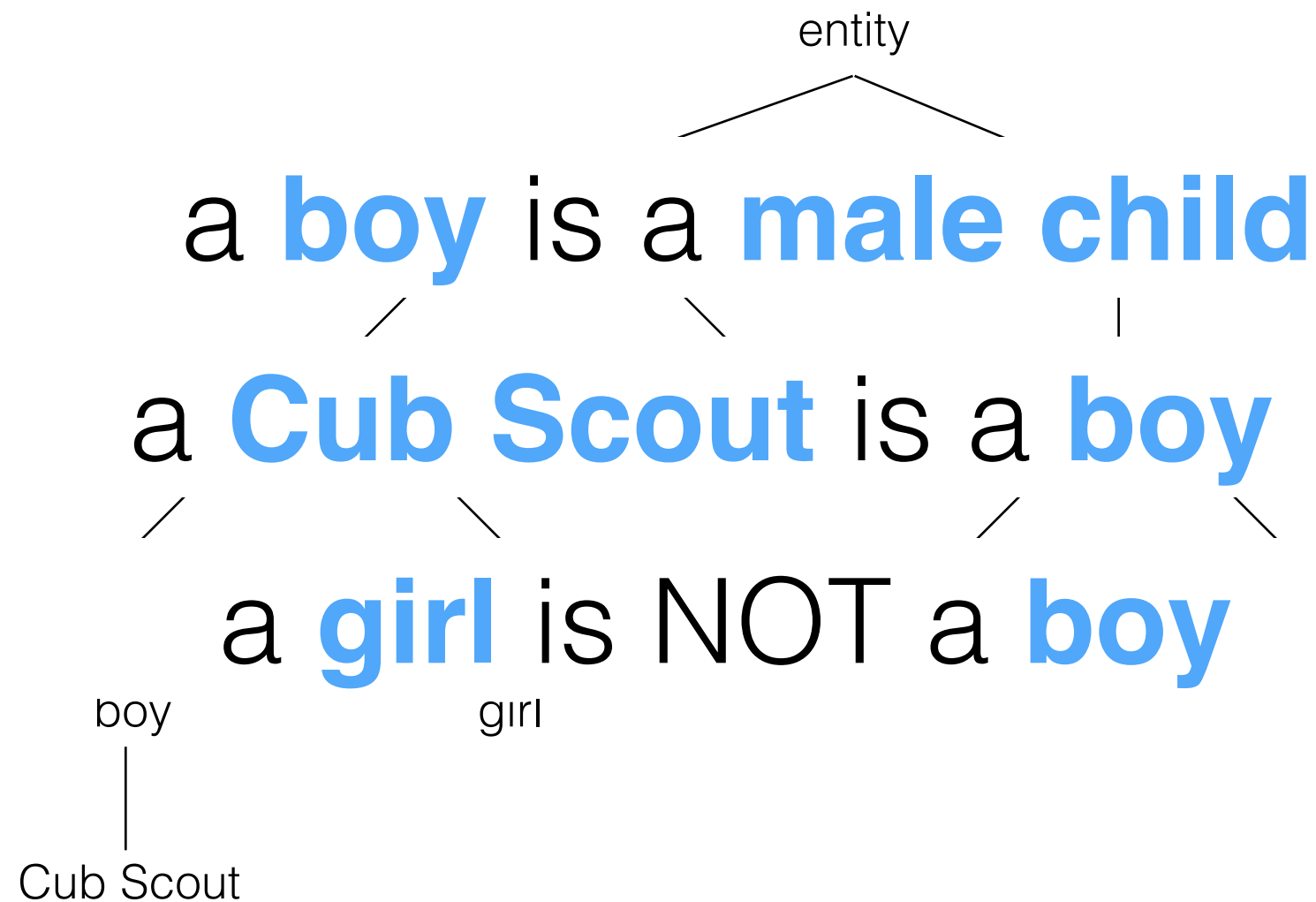
WordNet

# Lexical Semantics



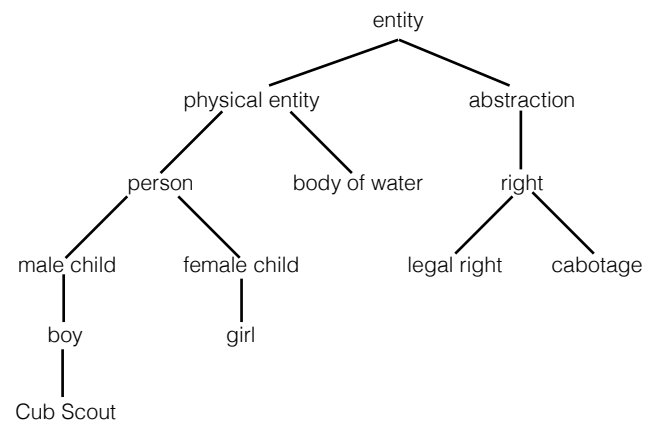
WordNet

# Lexical Semantics



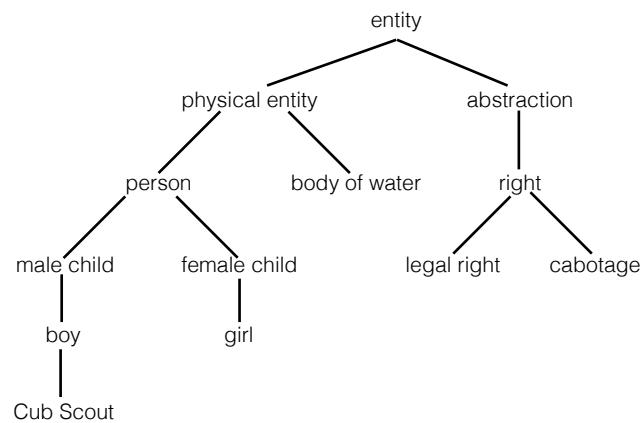
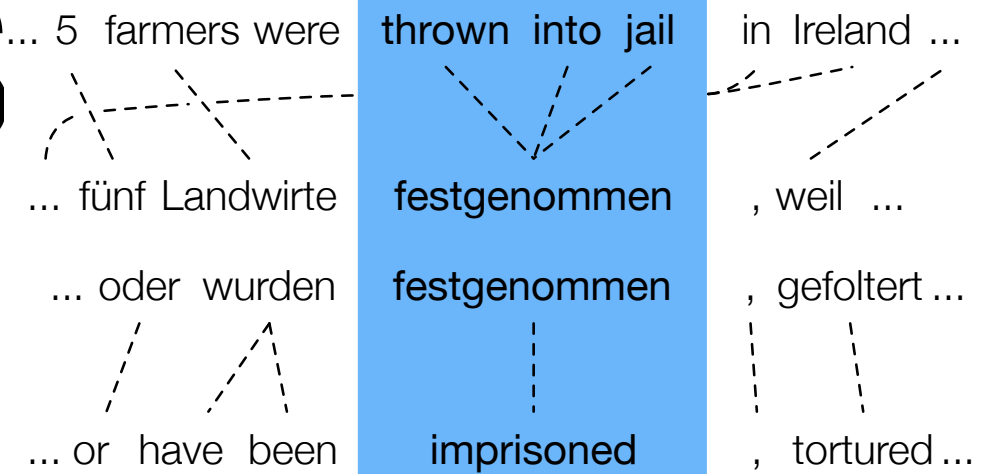
WordNet

# Lexical Semantics



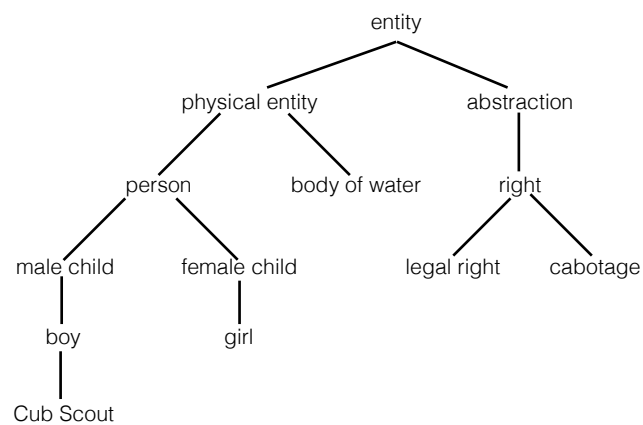
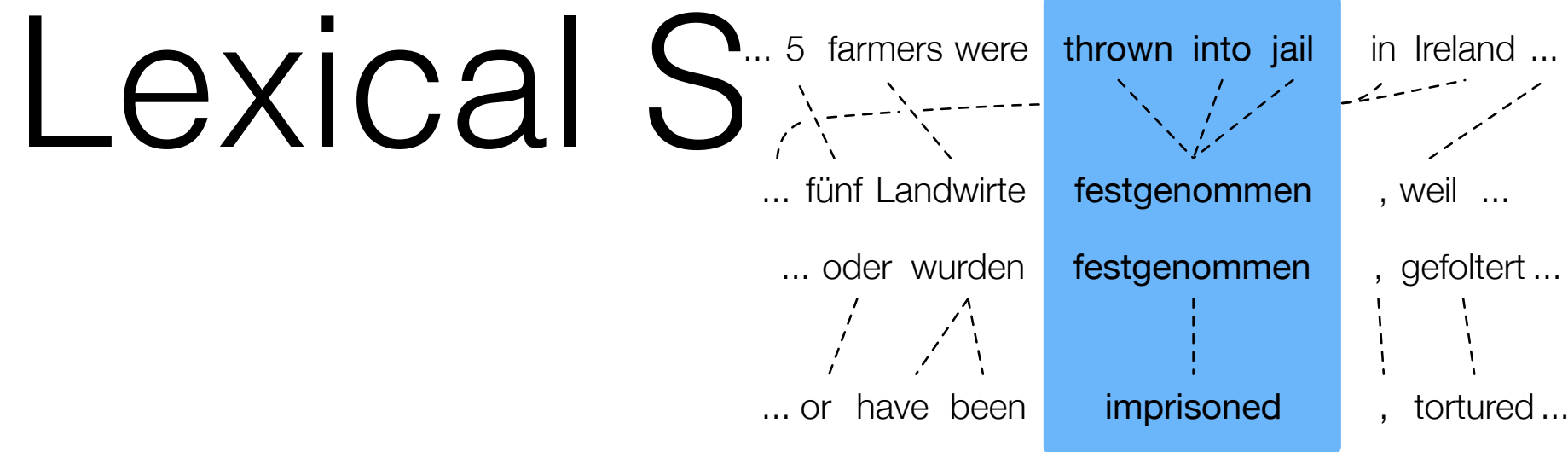
WordNet

# Lexical S



## WordNet

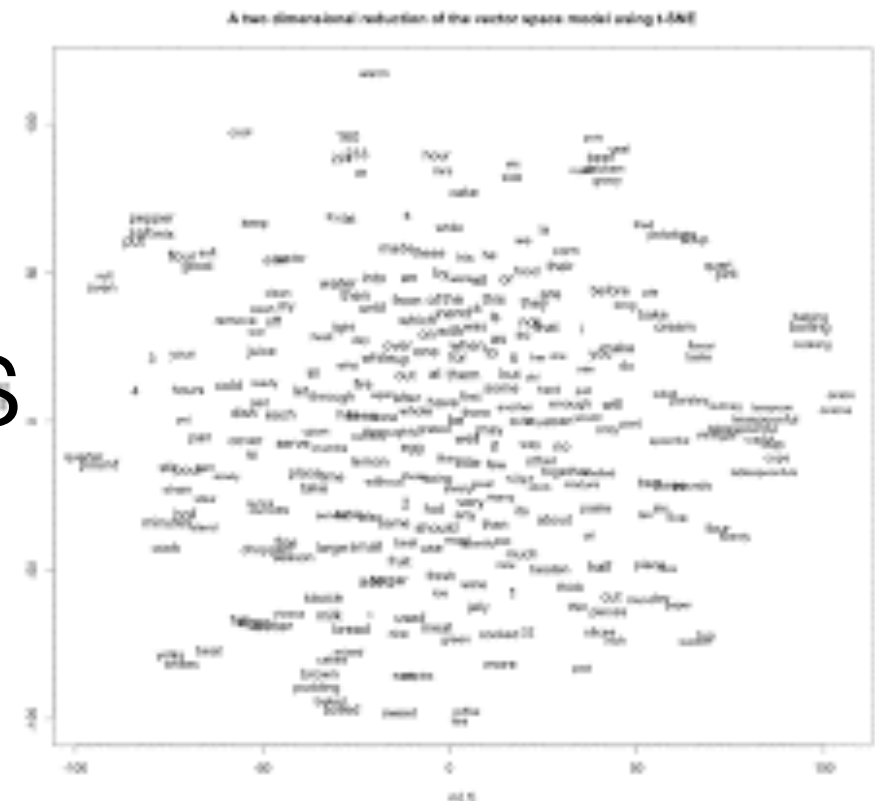
## Bilingual Pivoting (PPDB)



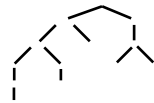
## Bilingual Pivoting (PPDB)

WordNet

Vector Space Models  
(word2vec)



# Lexical Semantics



boy	kid
boy	sons
boy	guys
boy	males
boy	son
boy	child
boy	boyfriend
boy	hans
boy	lad
boy	guy
boy	wraps
boy	gus
boy	bollocks
boy	teenager
boy	baby
boy	waiter
boy	men
boy	mandog
boy	buddy
boy	friend
boy	does
boy	pops
boy	youngster
boy	brother

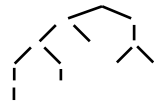
boy	girl
boy	dude
boy	fella
boy	laddie
boy	gentleman
boy	male
boy	youth
boy	juvenile
boy	toddler
boy	puppy
boy	fellow
boy	mate
boy	little
boy	bro
boy	bloke
boy	boss
boy	kiddo
boy	apprentice
boy	brat
boy	lapdog
boy	children
boy	bachelor
boy	soldier
boy	sweetheart

boy	doggy
boy	pup
boy	ah
boy	infant
boy	pooch
boy	yarn
boy	sonny
boy	childhood
boy	doggy
boy	servant
boy	grandson
boy	colt
boy	darling
boy	teen
boy	junior
boy	baby
boy	bit
boy	daughter
boy	foal
boy	bearer
boy	shorty
boy	foal
boy	chum
boy	blood

boy	mother
boy	mommy
boy	father
boy	student
boy	person
boy	type
boy	cheeky
boy	buster
boy	husband
boy	offspring
boy	wee
boy	idiot
boy	partner
boy	toy
boy	old-timer
boy	calf
boy	protege
boy	sage
boy	kitty
boy	bloodhound
boy	homie
boy	cub
boy	wolf
boy	honey



# Lexical Semantics



boy	kid	boy	girl	boy	doggy	boy	mother
boy	sons	boy	dude	boy	pup	boy	mommy
boy	guys	boy	fella	boy	ah	boy	father
boy	males	boy	laddie	boy	infant	boy	student
boy	son	boy	gentleman	boy	pooch	boy	person
boy	child	boy	male	boy	yarn	boy	type
boy	boyfriend	boy	youth	boy	sonny	boy	cheeky
boy	hans	boy	juvenile	boy	childhood	boy	buster
boy	ba	boy	lad	boy	doggy	boy	husband
boy	guy	boy	puppy	boy	servant	boy	offspring
boy	wraps	boy	fellow	boy	grandson	boy	wee
boy	gus	boy	mate	boy	colt	boy	idiot
boy	bollocks	boy	little	boy	darling	boy	partner
boy	teenager	boy	bro	boy	teen	boy	toy
boy	baby	boy	bloke	boy	junior	boy	old-timer
boy	waiter	boy	boss	boy	baby	boy	calf
boy	men	boy	kiddo	boy	bit	boy	protege
boy	mandog	boy	apprentice	boy	daughter	boy	sage
boy	buddy	boy	brat	boy	foal	boy	kitty
boy	friend	boy	lapdog	boy	bearer	boy	bloodhound
boy	does	boy	children	boy	shorty	boy	homie
boy	pops	boy	bachelor	boy	foal	boy	cub
boy	youngster	boy	soldier	boy	chum	boy	wolf
boy	brother	boy	sweetheart	boy	blood	boy	honey

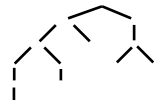
boy

kid

boy

person

# Lexical Semantics

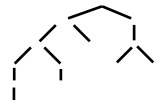


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boy	son	boy	gentleman	boy	pooch	boy	person
boy	child	boy	male	boy	yarn	boy	type
boy	boyfriend	boy	youth	boy	sonny	boy	cheeky
boy	hans	boy	juvenile	boy	childhood	boy	buster
boy	lad	boy	toddler	boy	doggy	boy	husband
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boy	waiter	boy	boss	boy	baby	boy	calf
boy	men	boy	kiddo	boy	bit	boy	protege
boy	mandog	boy	apprentice	boy	daughter	boy	sage
boy	buddy	boy	brat	boy	foal	boy	kitty
boy	friend	boy	lapdog	boy	bearer	boy	bloodhound
boy	does	boy	children	boy	shorty	boy	homie
boy	pops	boy	bachelor	boy	foal	boy	cub
boy	youngster	boy	soldier	boy	chum	boy	wolf
boy	brother	boy	sweetheart	boy	blood	boy	honey

boy | girl

boy | puppy

# Lexical Semantics



boy # toddler

boy # idiot

boy	kid	boy	girl	boy	doggy	boy	mother
boy	sons	boy	dude	boy	pup	boy	mommy
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boy	gus	boy	mate	boy	colt	boy	idiot
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boy	men	boy	kiddo	boy	bit	boy	protege
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# The Paraphrase Database

boy	kid	boy	girl	boy	doggy	boy	mother
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boy	guys	boy	fella	boy	ah	boy	father
boy	males	boy	laddie	boy	infant	boy	student
boy	son	boy	gentleman	boy	pooch	boy	person
boy	child	boy	male	boy	yarn	boy	type
boy	boyfriend	boy	youth	boy	sonny	boy	cheeky
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boy	men	boy	kiddo	boy	bit	boy	protege
boy	dog	boy	apprentice	boy	daughter	boy	sage
boy	buddy	boy	brat	boy	foal	boy	kitty
boy	friend	boy	lapdog	boy	bearer	boy	bloodhound
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boy	son	boy	gentleman	boy	pooch	boy	person
boy	child	boy	male	boy	yarn	boy	type
boy	boyfriend	boy	youth	boy	sonny	boy	cheeky
boy	hans	boy	juvenile	boy	childhood	boy	buster
boy	lad	boy	toddler	boy	doggy	boy	husband
boy	guy	boy	puppy	boy	servant	boy	offspring
boy	wraps	boy	fellow	boy	grandson	boy	wee
boy	gus	boy	mate	boy	colt	boy	idiot
boy	bollocks	boy	little	boy	darling	boy	partner
boy	teenager	boy	bro	boy	teen	boy	toy
boy	baby	boy	bloke	boy	junior	boy	old-timer
boy	waiter	boy	boss	boy	baby	boy	calf
boy	men	boy	kiddo	boy	bit	boy	protege
boy	dog	boy	apprentice	boy	daughter	boy	sage
boy	buddy	boy	brat	boy	foal	boy	kitty
boy	friend	boy	lapdog	boy	bearer	boy	bloodhound
boy	does	boy	children	boy	shorty	boy	homie
boy	pops	boy	bachelor	boy	foal	boy	cub
boy	youngster	boy	soldier	boy	chum	boy	wolf
boy	brother	boy	sweetheart	boy	blood	boy	honey

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boy	kid
boy	sons
boy	guys
boy	males
boy	son
boy	child
boy	boyfriend
boy	hans
boy	lad
boy	guy
boy	wraps
boy	gus
boy	bollocks
boy	teenager
boy	baby
boy	waiter
boy	men
boy	dog
boy	buddy
boy	friend
boy	does
boy	pops
boy	youngster
boy	brother

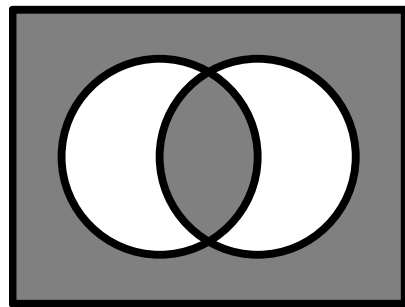
boy	girl
boy	dude
boy	fella
boy	laddie
boy	gentleman
boy	male
boy	youth
boy	juvenile
boy	toddler
boy	puppy
boy	fellow
boy	mate
boy	little
boy	bro
boy	bloke
boy	boss
boy	kiddo
boy	apprentice
boy	brat
boy	lapdog
boy	children
boy	bachelor
boy	soldier
boy	sweetheart

boy	sonny
boy	yarn
boy	sonny
boy	childhood
boy	doggy
boy	servant
boy	grandson
boy	colt
boy	darling
boy	teen
boy	junior
boy	baby
boy	bit
boy	daughter
boy	foal
boy	bearer
boy	shorty
boy	foal
boy	chum
boy	blood

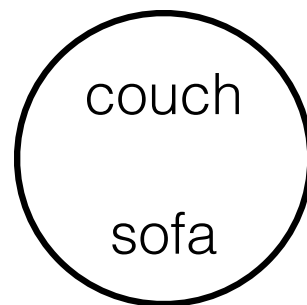
boy	mother
boy	sonny
boy	husband
boy	offspring
boy	wee
boy	idiot
boy	partner
boy	toy
boy	old-timer
boy	calf
boy	protege
boy	sage
boy	kitty
boy	bloodhound
boy	homie
boy	cub
boy	wolf
boy	honey

~100M word  
and phrase pairs

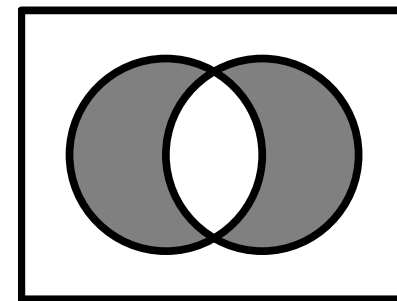
equivalence



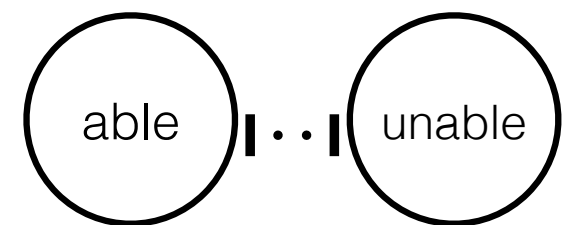
synonym



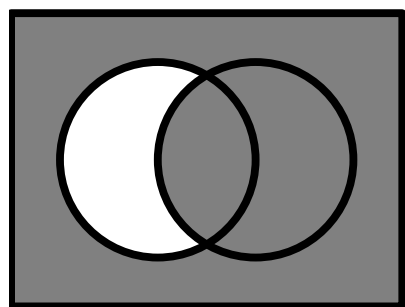
negation



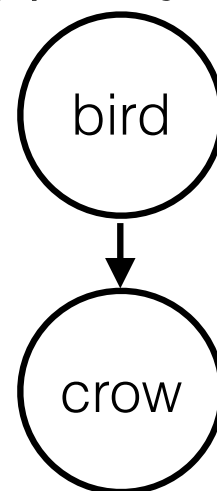
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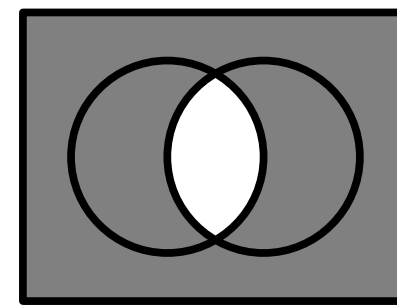
forward  
entailment



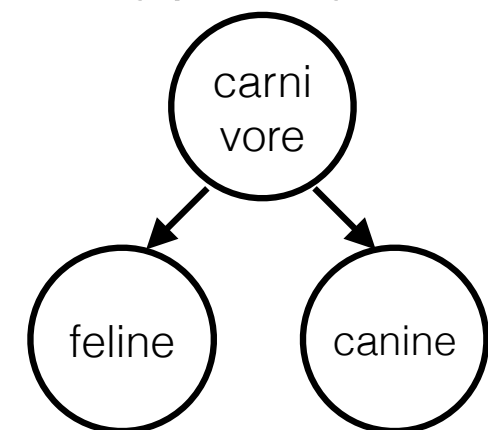
hyponymy



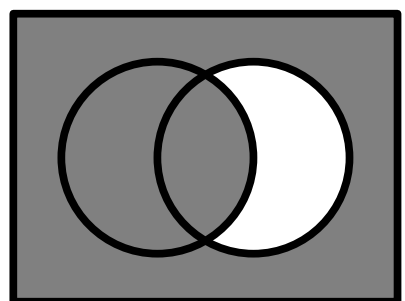
alternation



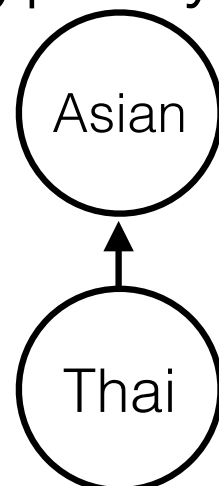
shared  
hypernym



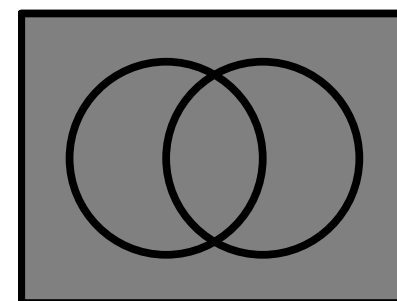
reverse  
entailment



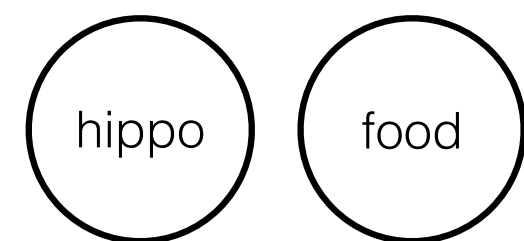
hypernymy



independence

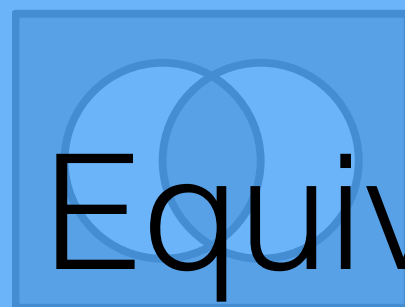


no path



equivalence

synonym



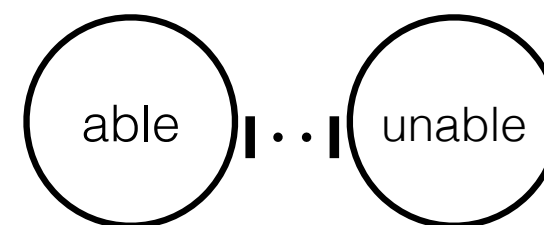
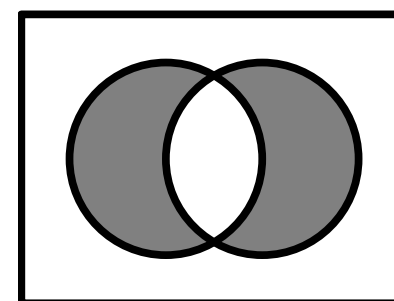
# Equivalence

couch

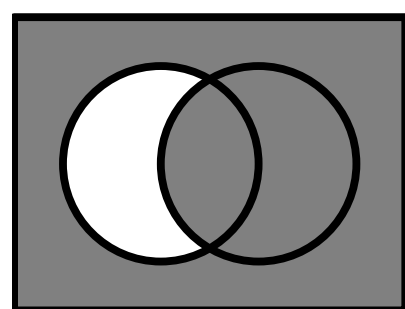
sofa

negation

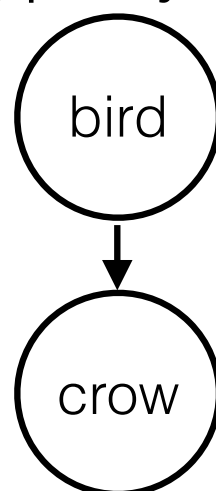
antonym



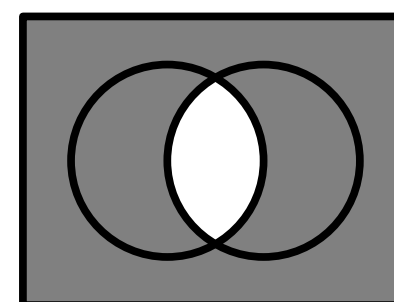
forward  
entailment



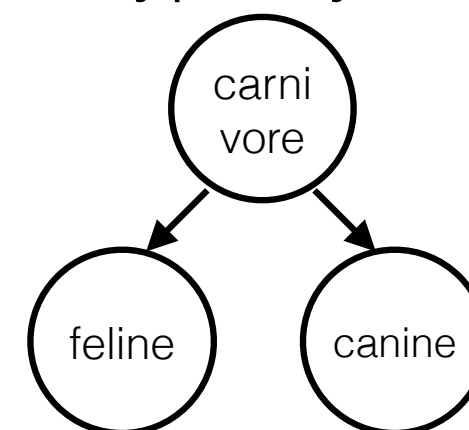
hyponymy



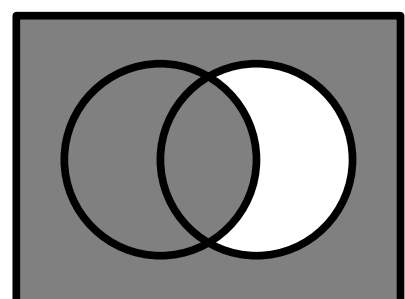
alternation



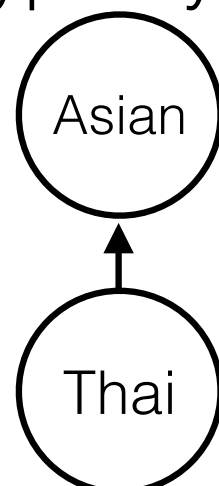
shared  
hypernym



reverse  
entailment

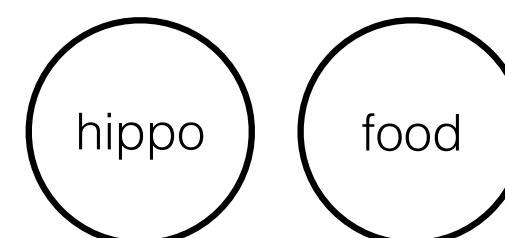
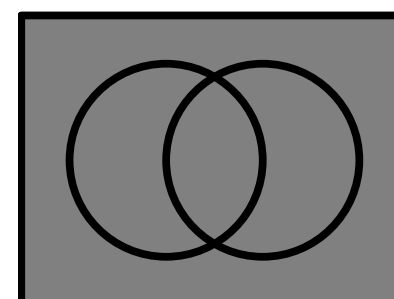


hypernymy



independence

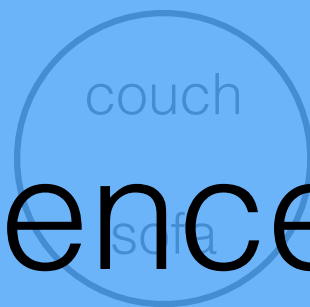
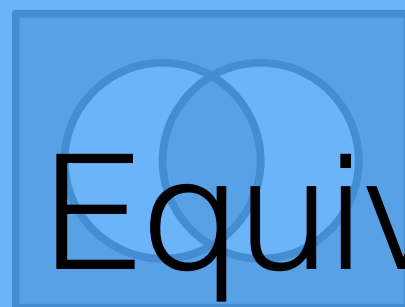
no path





equivalence

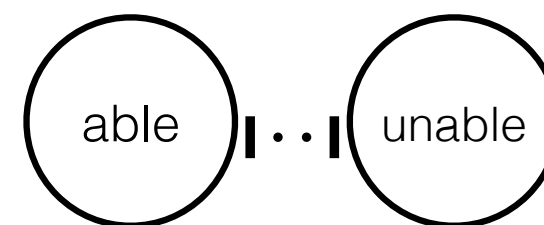
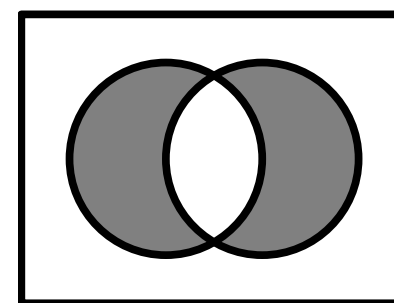
synonym



# Equivalence

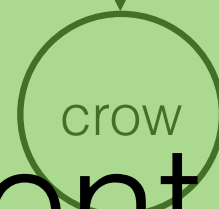
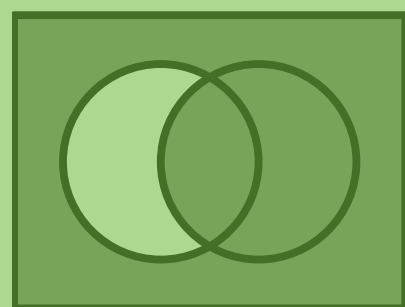
negation

antonym



forward  
entailment

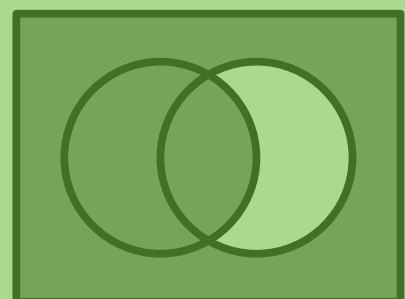
hyponymy



# Entailment

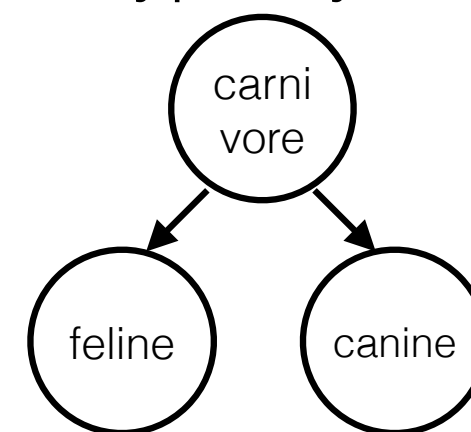
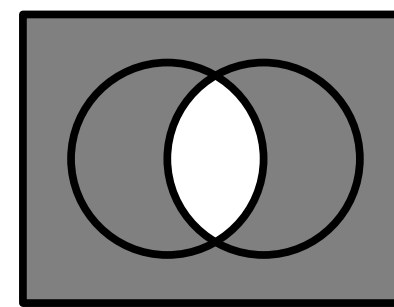
reverse  
entailment

hypernymy



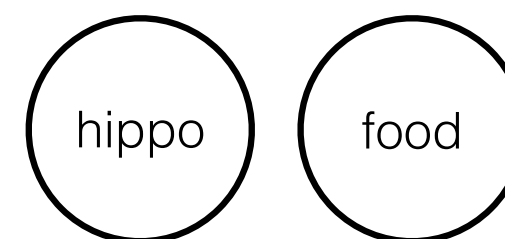
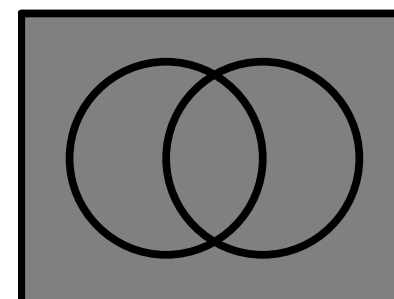
alternation

shared  
hypernym



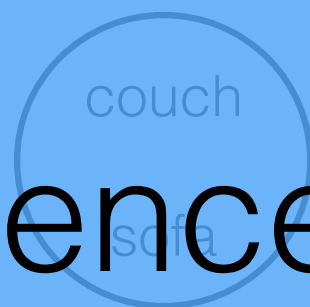
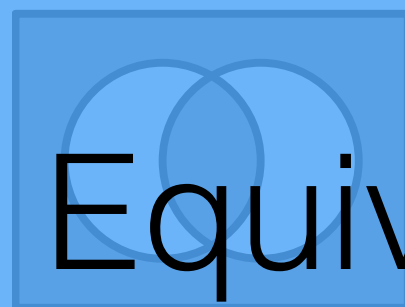
independence

no path



equivalence

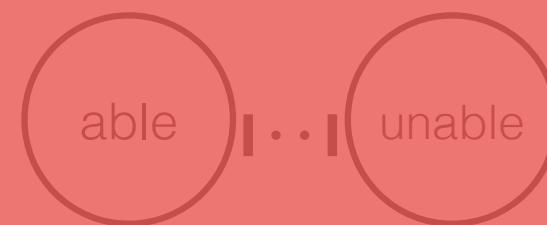
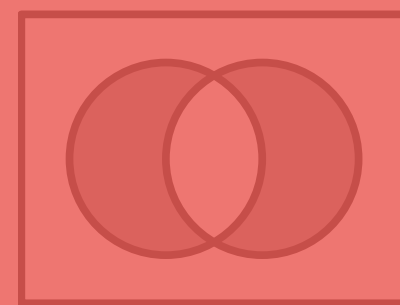
synonym



# Equivalence

negation

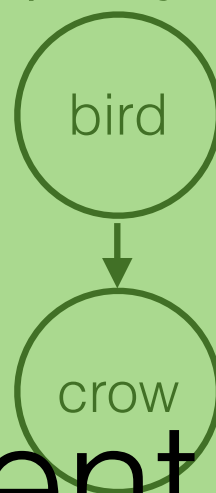
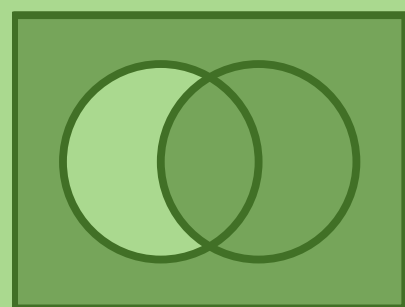
antonym



# Exclusion

forward  
entailment

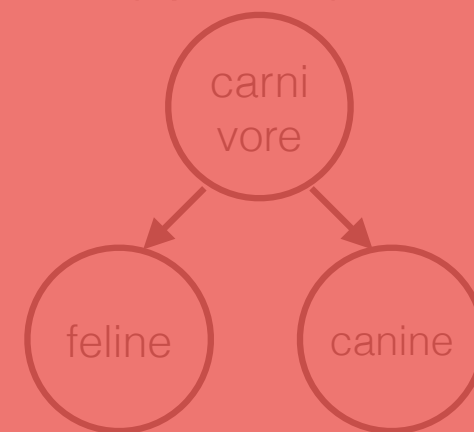
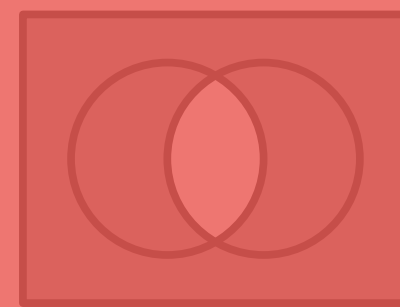
hyponymy



# Entailment

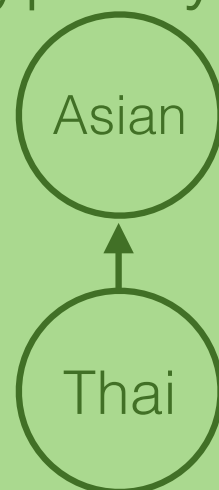
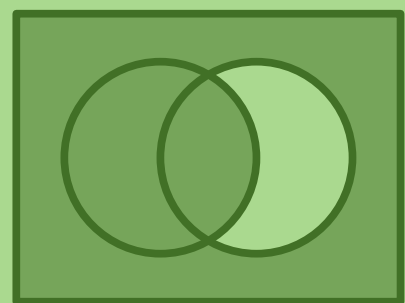
alternation

shared  
hypernym



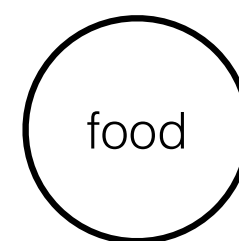
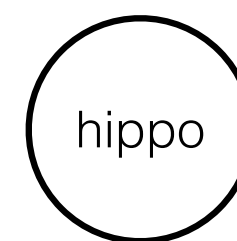
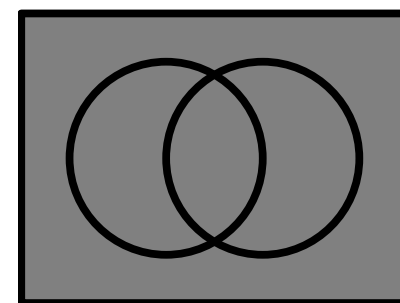
reverse  
entailment

hypernymy



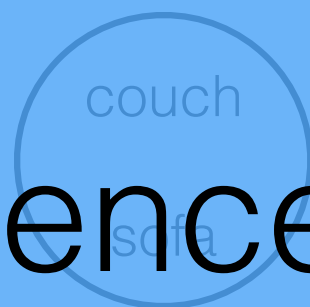
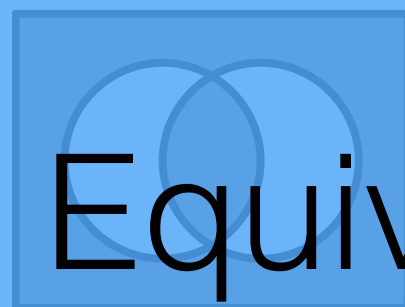
independence

no path



equivalence

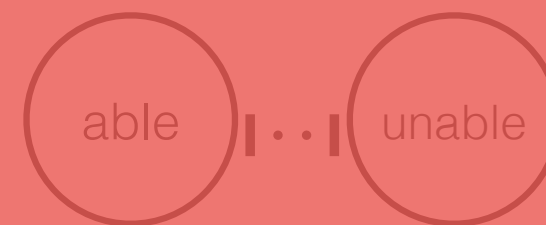
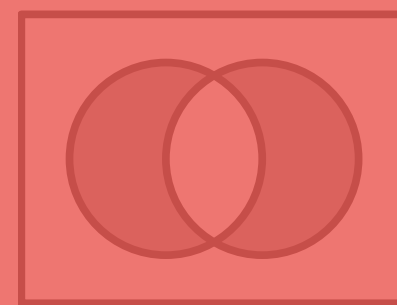
synonym



# Equivalence

negation

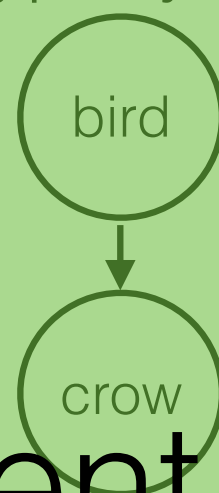
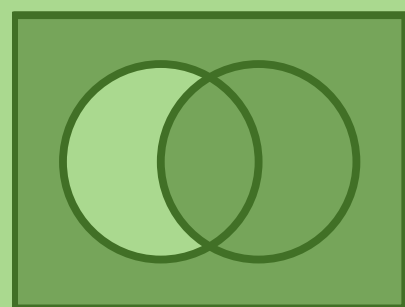
antonym



# Exclusion

forward  
entailment

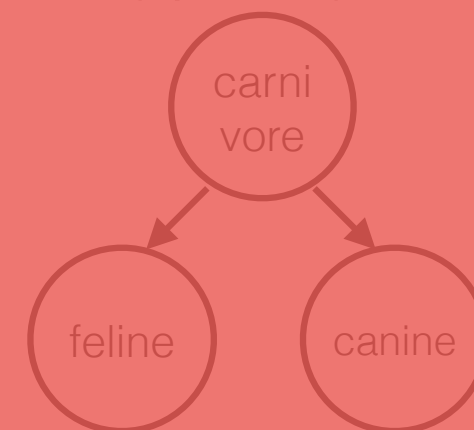
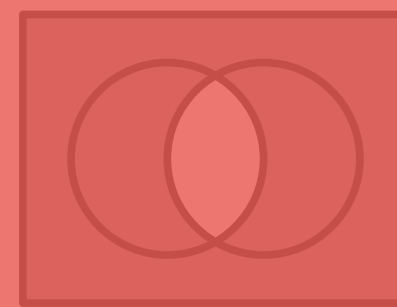
hyponymy



# Entailment

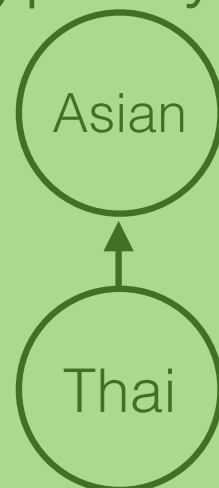
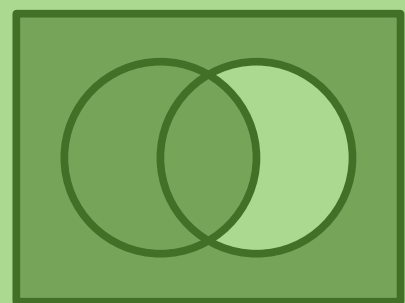
alternation

shared  
hypernym



reverse  
entailment

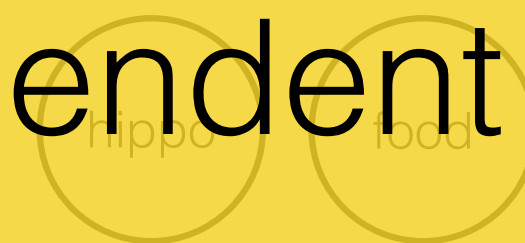
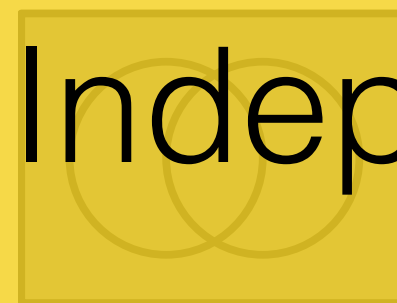
hypernymy



independence

no path

# Independent



# Monolingual Features

symmetric and asymmetric similarities based on  
dependency context

		nsubj-draw	lost-dep	nsubj-vomit	poss-shoe	dep-brother	nsubjpass-buckled	nsubj-yell	rcmod-tired	...			
little girl		1	1	1	1	1	0	0	1	0	0	1	0
kid		1	0	1	0	1	1	1	1	1	1	1	1

cosine:0.431 lin:0.544

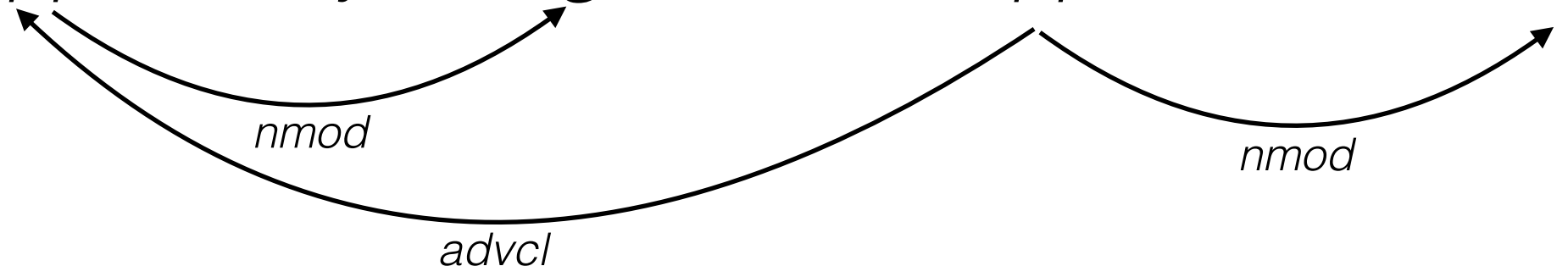
balprec:0.396 weeds:0.289...

*Discovery of Inference Rules from Text. (Lin and Pantel SIGKDD 2001)*

# Monolingual Features

lexico-syntactic patterns

*...if this can happen to my **little girl** , it can happen to other **kids**...*



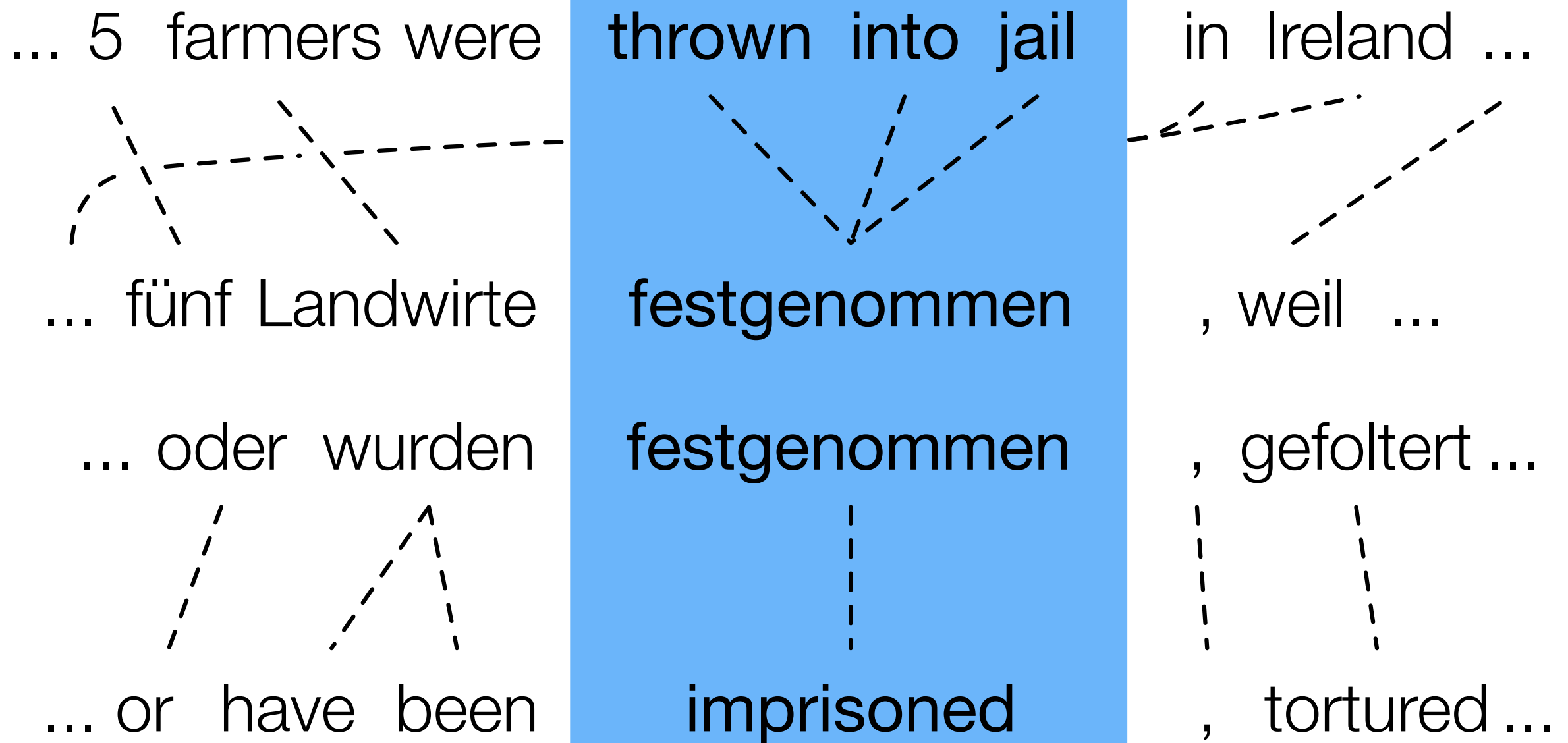
`[X] <-nmod- [happen] -advcl-> [happen] -nmod-> [Y] : 1`

`[X] <-conj- [Y] : 1`

`[X] <-pobj- [as] <-prep- [know] <-rcmod- [Y] : 1`

*Automatic acquisition of hyponyms from large text corpora. (Hearst COLING 1992)*  
*Semantic taxonomy induction from heterogenous evidence. (Snow et al. ACL 2006)*

# Bilingual Features



*Paraphrasing with bilingual parallel corpora. (Bannard and Callison-Burch ACL 2005)*

*PPDB: The paraphrase database. (Ganitkevitch et al. NAACL 2013)*

equiv. entail. excl. other indep.

equiv.	58%	20%	4%	15%	3%
entail.	20%	51%	3%	18%	7%
excl.	26%	14%	37%	17%	6%
other	8%	13%	2%	71%	6%
indep.	15%	21%	5%	36%	23%

Monolingual  
features  
only

equiv.	62%	21%	5%	4%	8%
entail.	27%	5%	7%	7%	54%
excl.	6%	14%	30%	36%	14%
other	1%	7%	6%	78%	8%
indep.	8%	19%	9%	30%	35%

Bilingual  
features  
only

equiv. entail. excl. other indep.

equiv.	58%	20%	4%	15%	3%
entail.	20%	51%	3%	18%	7%
excl.	26%	14%	37%	17%	6%
other	8%	13%	2%	71%	6%
indep.	15%	21%	5%	36%	23%

Monolingual  
features  
only

equiv.	62%	21%	5%	4%	8%
entail.	27%	5%	7%	7%	54%
excl.	6%	14%	30%	36%	14%
other	1%	7%	6%	78%	8%
indep.	8%	19%	9%	30%	35%

Bilingual  
features  
only



equiv. entail. excl. other indep.

equiv.	58%	20%	4%	15%	3%
entail.	20%	51%	3%	18%	7%
excl.	26%	14%	37%	17%	6%
other	8%	13%	2%	71%	6%
indep.	15%	21%	5%	36%	23%

Monolingual  
features  
only

equiv.	62%	21%	5%	4%	8%
entail.	27%	5%	7%	7%	54%
excl.	6%	14%	30%	36%	14%
other	1%	7%	6%	78%	8%
indep.	8%	19%	9%	30%	35%

Bilingual  
features  
only

	equiv.	entail.	excl.	other	indep.
equiv.	83%	10%	0%	2%	4%
entail.	6%	76%	2%	7%	8%
excl.	2%	8%	73%	13%	3%
other	1%	4%	2%	88%	6%
indep.	5%	10%	3%	18%	64%

All features

Equivalent	Entailment	Exclusion	Other	Independent
look at/ watch	little girl/girl	close/open	swim/water	girl/play
a person/ someone	kuwait/ country	minimal/ significant	husband/ marry	found/party
clean/ cleanse	tower/ building	boy/young girl	oil/oil price	man/talk
distant/ remote	sneaker/ footwear	nobody/ someone	country/ patriotic	profit/year
phone/ telephone	heroin/drug	blue/green	drive/ vehicle	holiday/ series
last autumn/ last fall	typhoon/ storm	france/ germany	playing/toy	city/south

*Adding Semantics to Data-Driven Paraphrasing. (Pavlick et al. ACL 2015)*

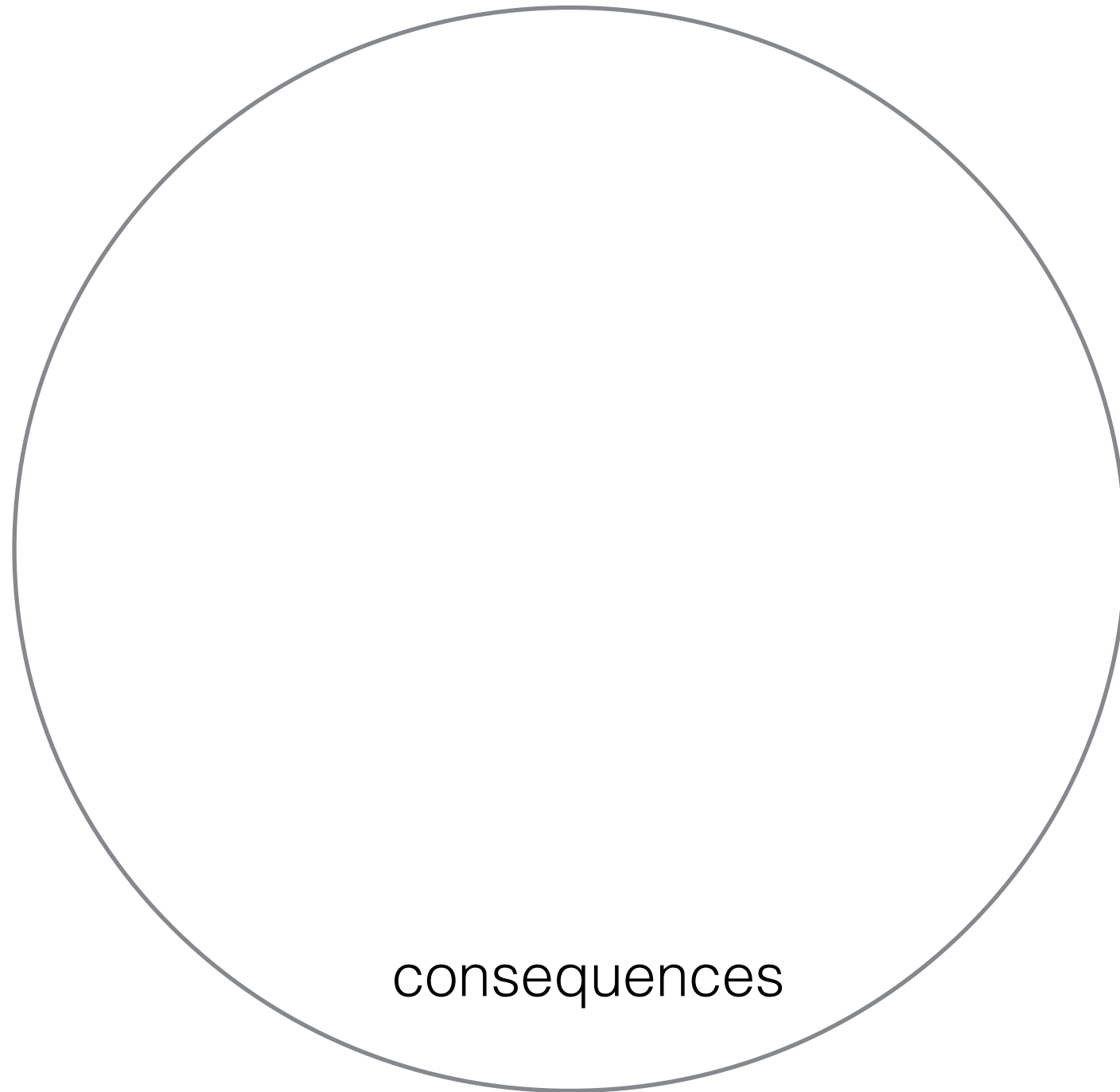
# INS(**environmental**)

Last December they had argued that the council had failed to consider possible **effects** of contaminated land at the site.

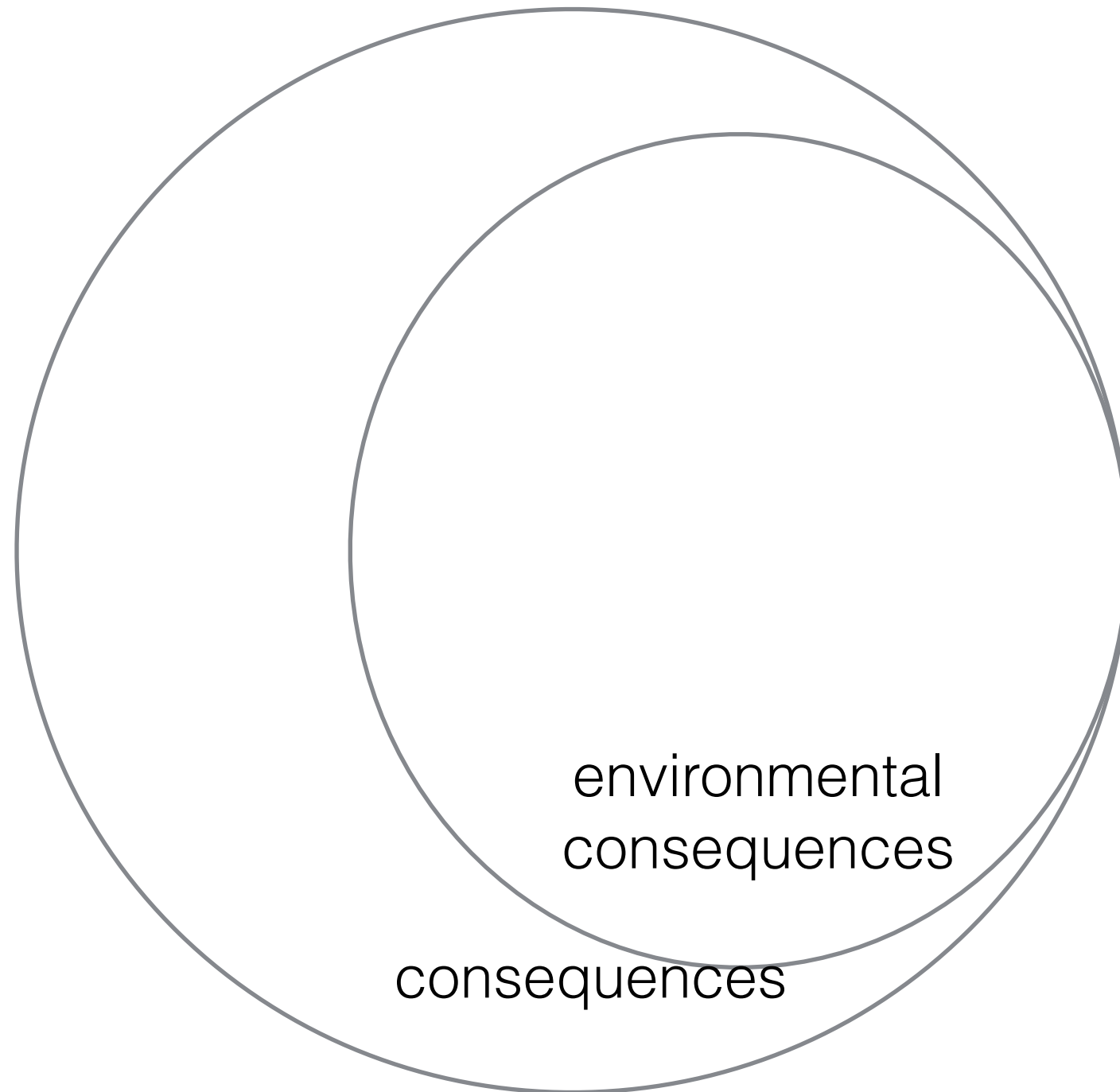
The council considered **environmental** consequences.

## **modifiers**

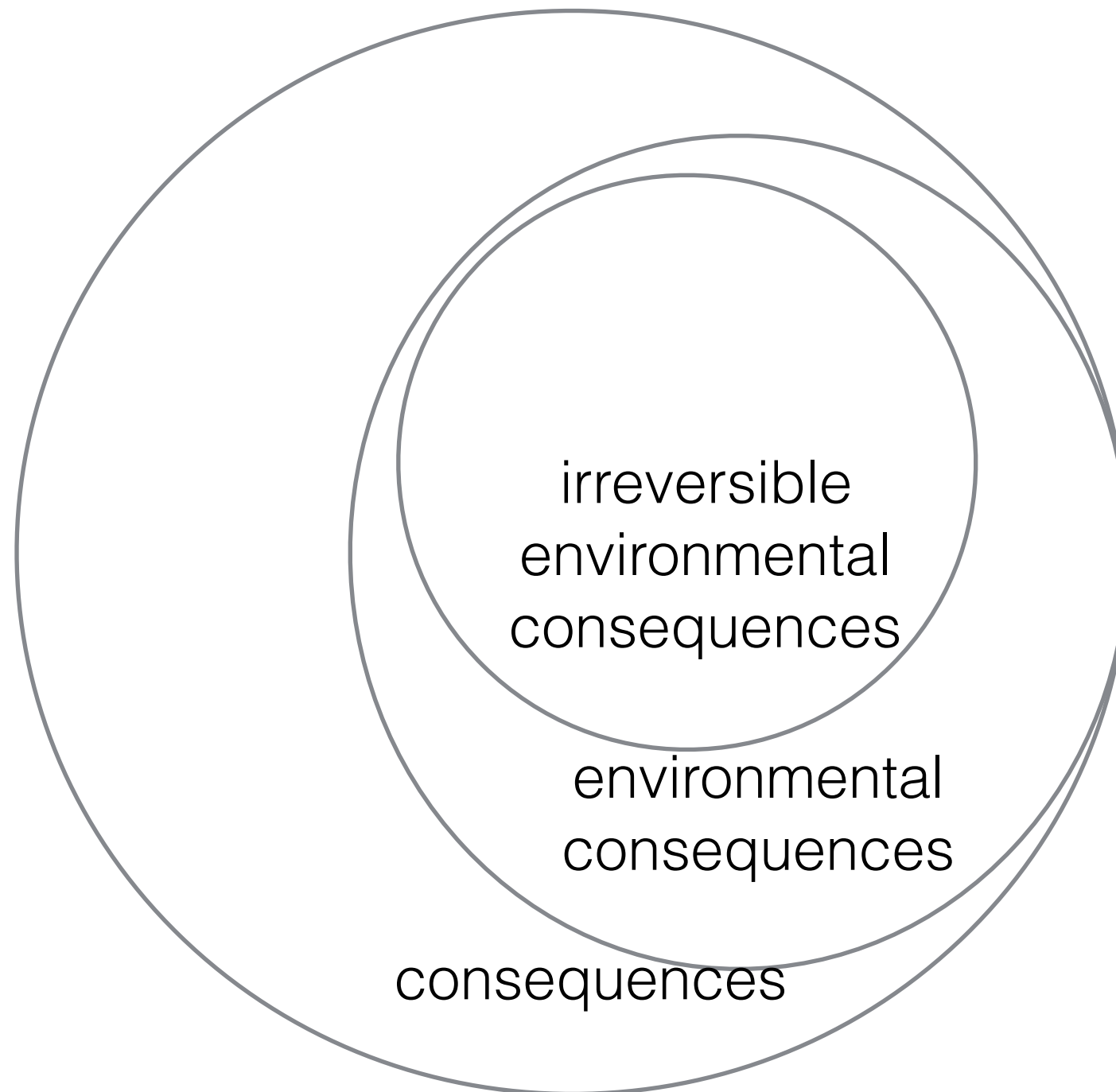
# Denotational Semantics



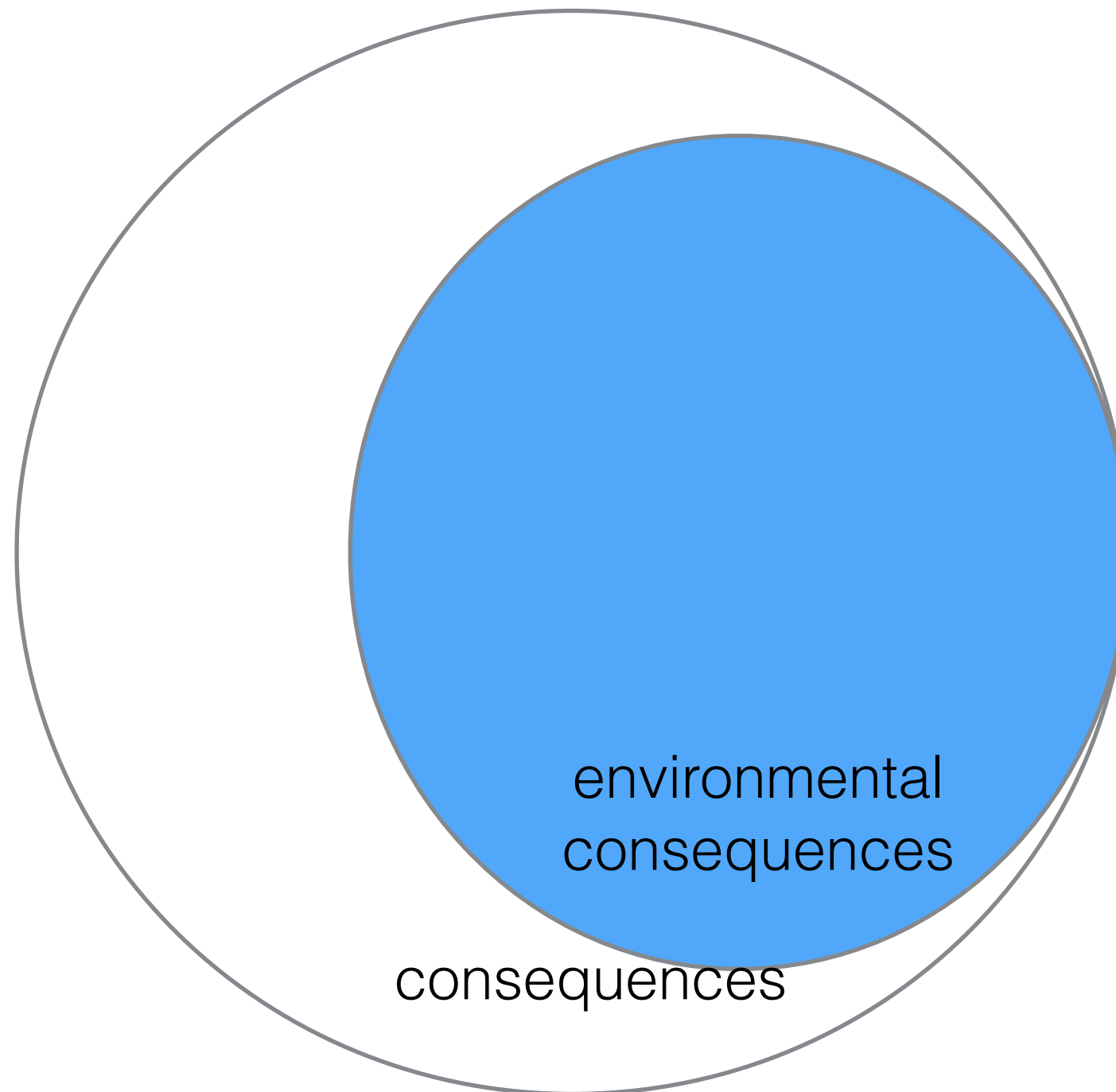
# Denotational Semantics



# Denotational Semantics



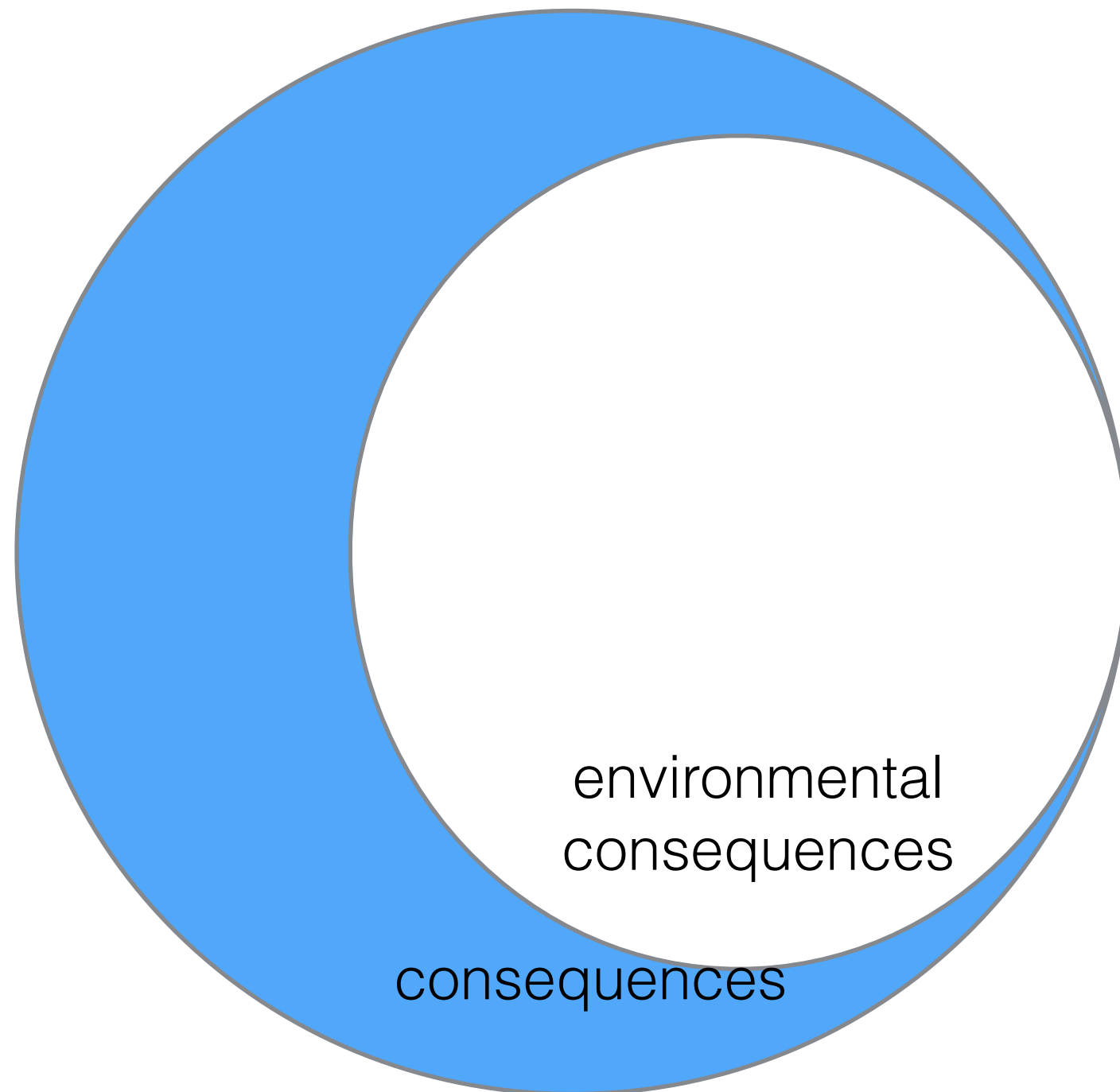
# Denotational Semantics



Does **environmental consequence**  
entail **consequence**?



# Denotational Semantics



Does **consequence**  
entail **environmental consequence**?

# Natural Language Inference

A man is pointing at a silver sedan.

A man is pointing at a **silver** car. SUB(sedan, car) ☐ yes

A man is pointing at a car. DEL(**silver**) ☒ yes

No man is pointing at a car.

# Natural Language Inference

*From image descriptions to visual denotations.*

A man is pointing at a silver sedan. (Young et al. TACL 2014)

*Entailment above the word level in distributional semantics.*

*(Baroni et al. EACL 2012)*

A man is pointing at a <b>silver</b> car.	SUB(sedan, car)	<input type="checkbox"/>	yes
---	-----------------	--------------------------	-----

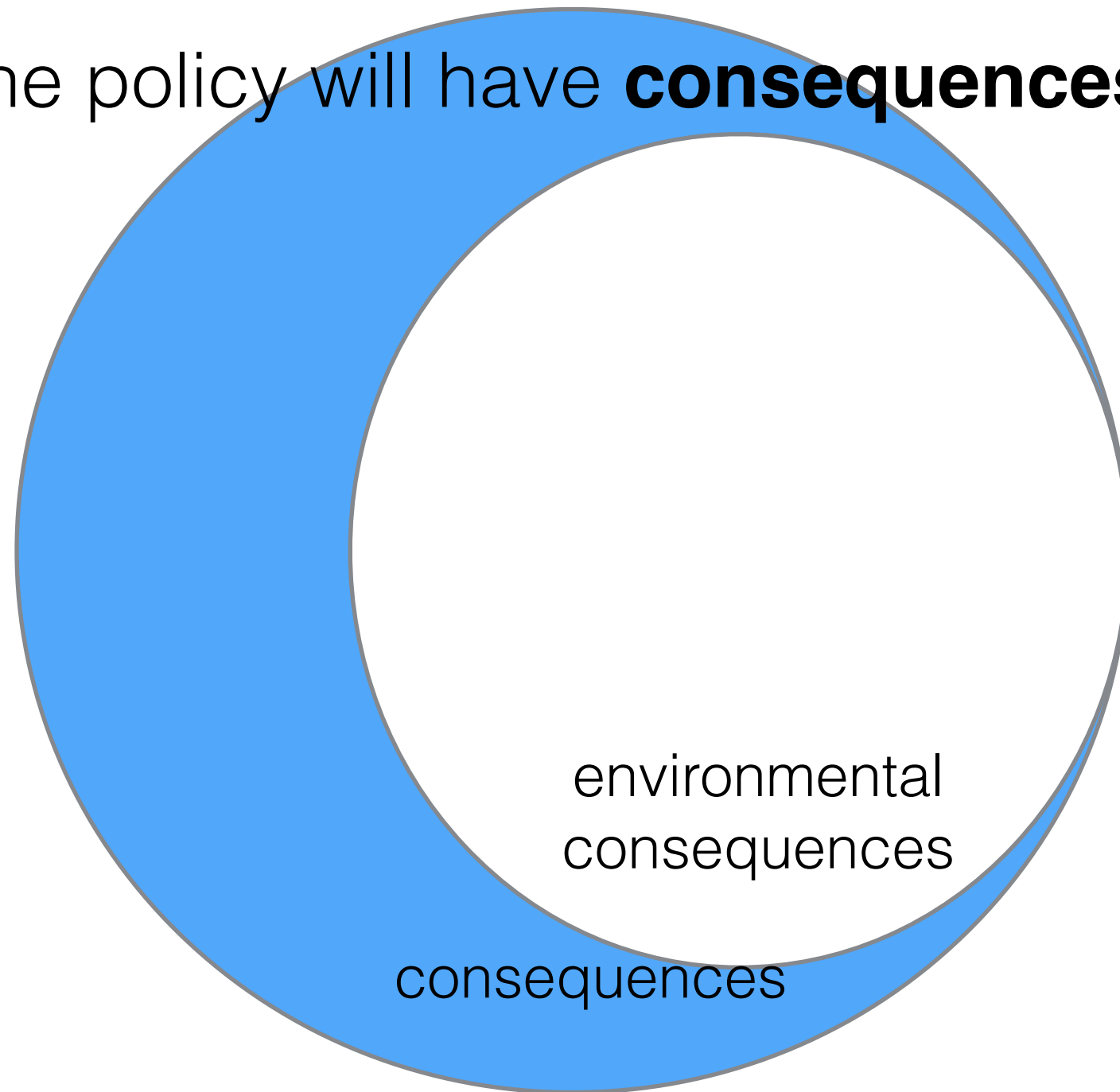
A man is pointing at a car.	DEL( <b>silver</b> )	<input checked="" type="checkbox"/>	yes
-----------------------------	----------------------	-------------------------------------	-----

*BIUTEE: A Modular Open-Source System for Recognizing Textual Entailment* (Stern and Dagan. ACL 2012)

*Natural Language Inference. (MacCartney PhD Thesis 2009)*

# Denotational Semantics

The policy will have **consequences**.

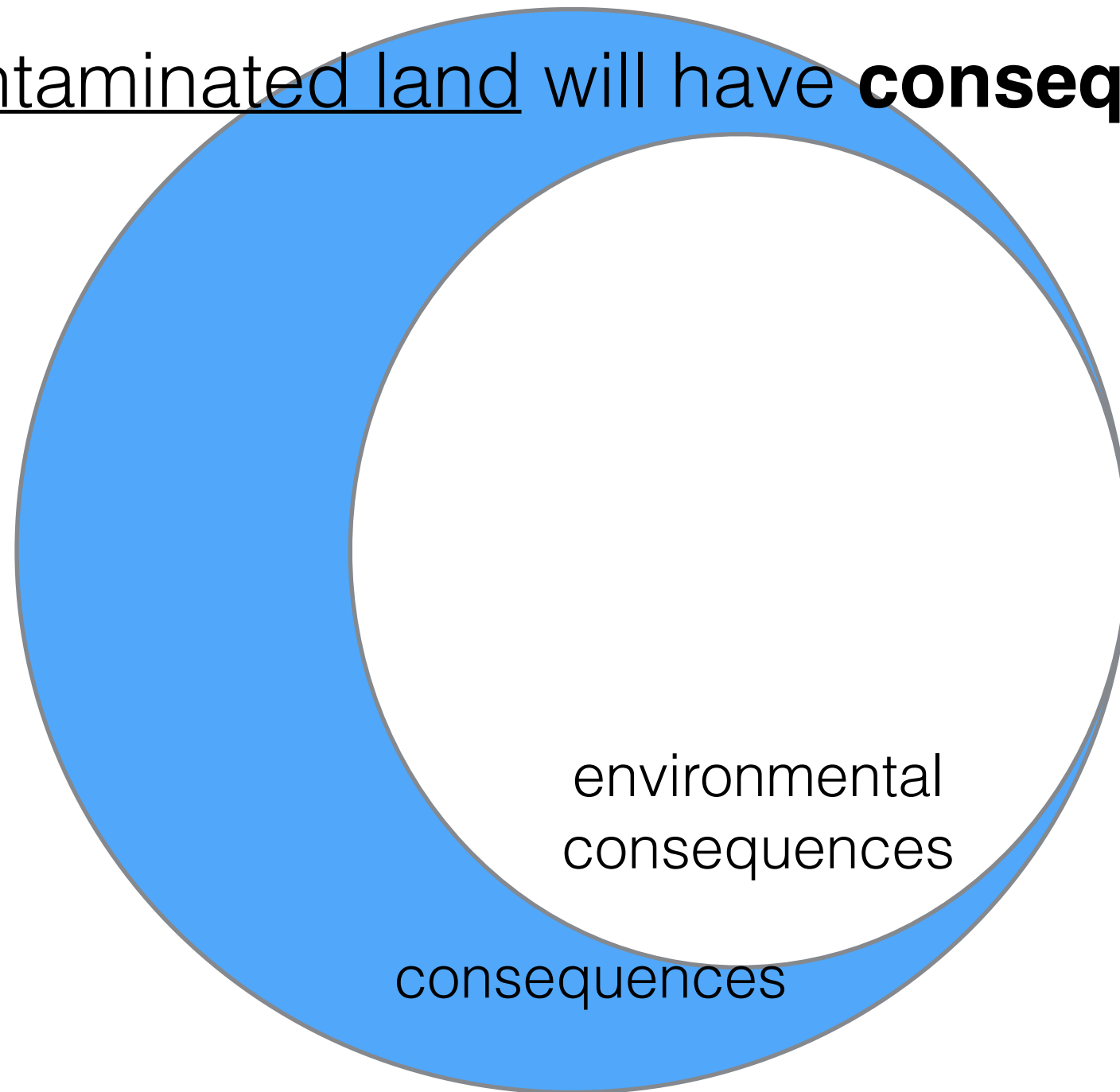


Does **consequence**  
entail **environmental consequence**?



# Denotational Semantics

The contaminated land will have **consequences**.



Does **consequence**  
entail **environmental consequence**?



# Natural Logic Entailment Relations

N does not entail AN

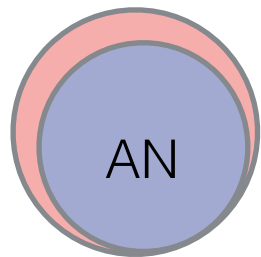
N does entail AN

# Natural Logic Entailment Relations

N does not entail AN

N does entail AN

Forward Entailment ( $AN \sqsubseteq N$ )



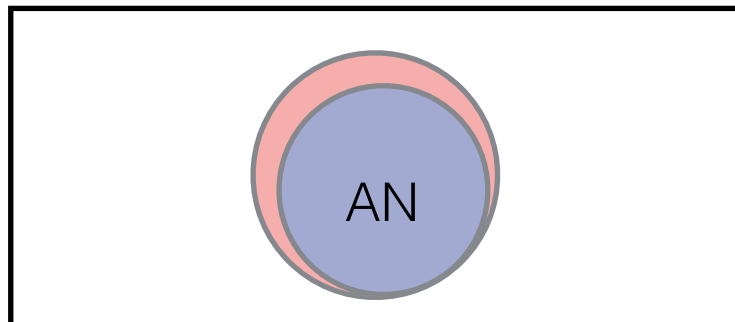
brown  
dog

# Natural Logic Entailment Relations

N does not entail AN

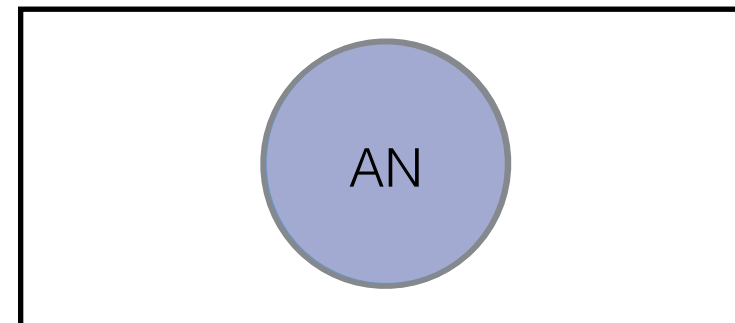
N does entail AN

Forward Entailment ( $AN \sqsubseteq N$ )



brown  
dog

Equivalence ( $AN \equiv N$ )



entire  
world

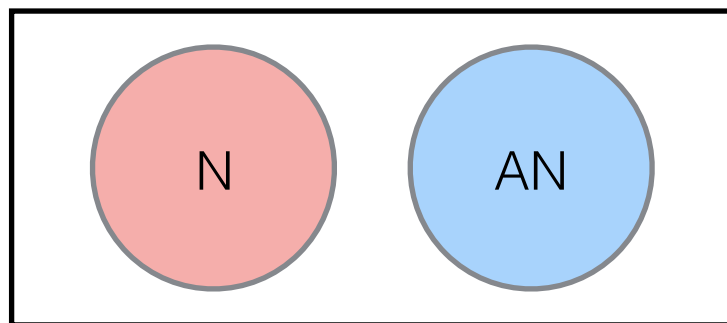


# Natural Logic Entailment Relations

N does not entail AN

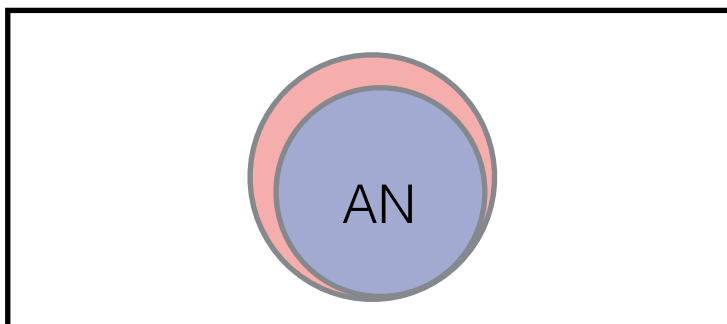
N does entail AN

Alternation ( $N \mid AN$ )



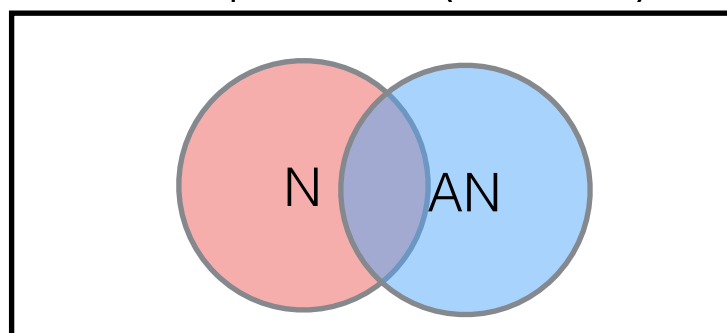
former  
senator

Forward Entailment ( $AN \sqsubseteq N$ )



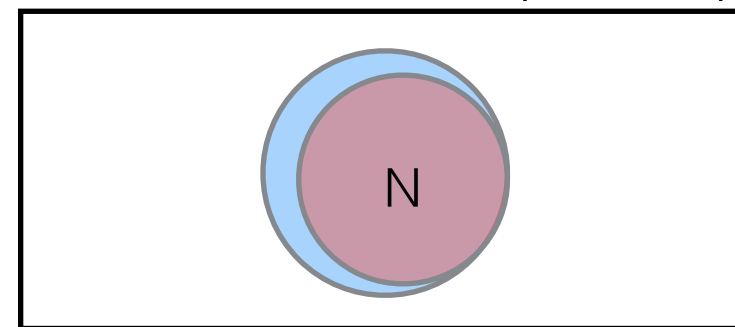
brown  
dog

Independent ( $N \# AN$ )



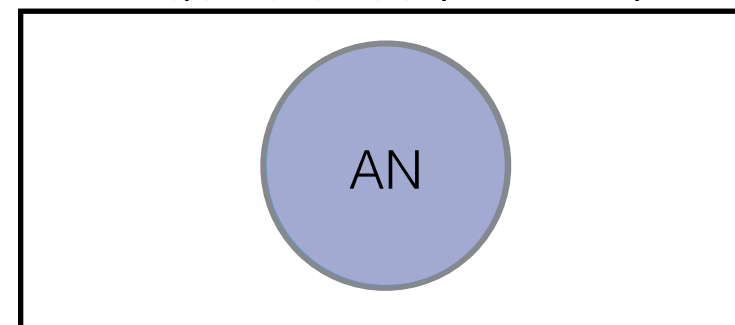
alleged  
criminal

Reverse Entailment ( $AN \supseteq N$ )



possible  
winner

Equivalence ( $AN \equiv N$ )



entire  
world

# Experimental Design

Wellers hopes the **system** will be fully operational by 2015 .

Wellers hopes the **financial system** will be fully operational by 2015 .

# Experimental Design

Wellers hopes the **system** will be fully operational by 2015 .

Wellers hopes the **financial system** will be fully operational by 2015 .

Contradiction

Entailment

Can't Tell

# Experimental Design

Wellers hopes the **financial system** will be fully operational by 2015 .

Wellers hopes the **system** will be fully operational by 2015 .

Contradiction

Entailment

Can't Tell

# Experimental Design

~200 human annotators  
~5,000 sentences  
4 genres

Watters hopes the **financial system** will be  
fully operational by 2015 .

Watters hopes the **system** will be fully  
operational by 2015 .

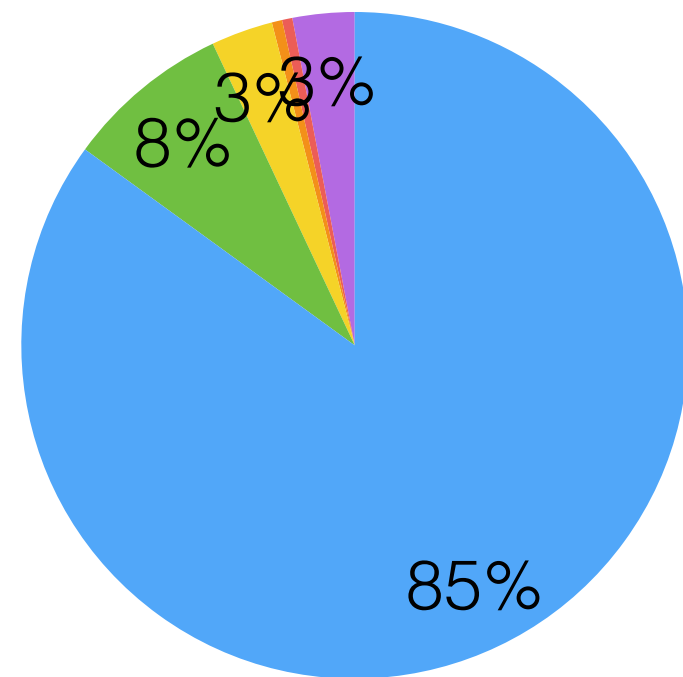
Contradiction

Entailment

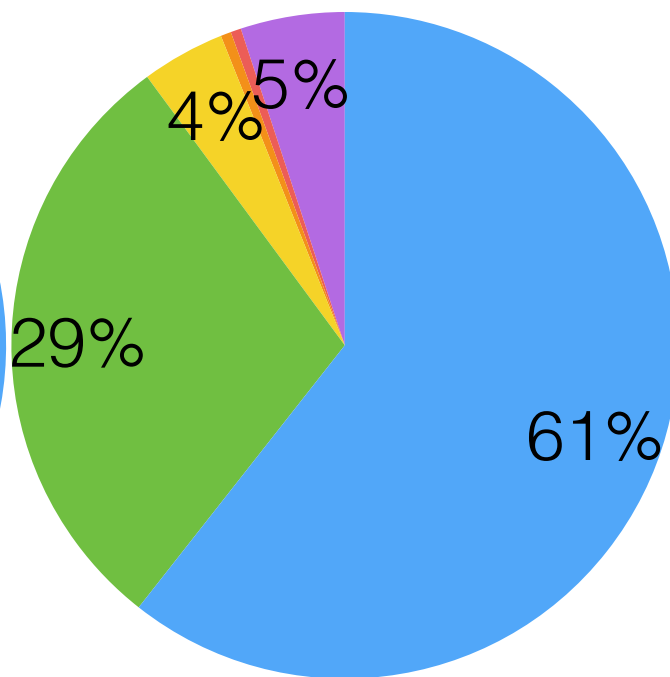
Can't Tell

# Empirical Analysis

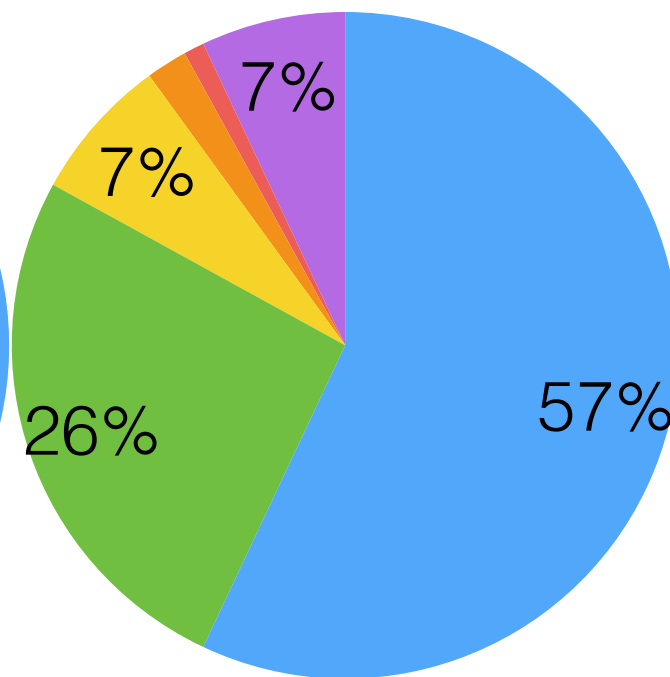
Image Captions



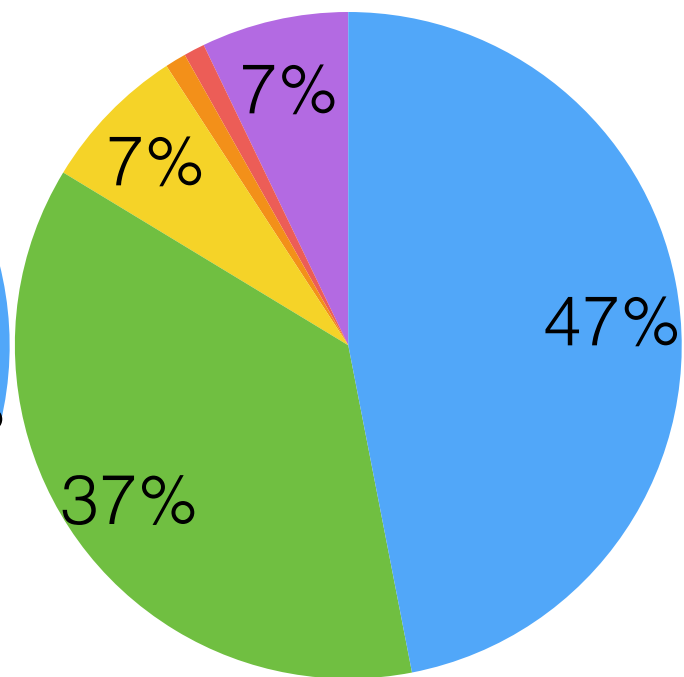
Literature



News



Forums



● AN < N    ● AN = N    ● AN # N    ● AN > N    ● AN | N    ● None

# Empirical Analysis

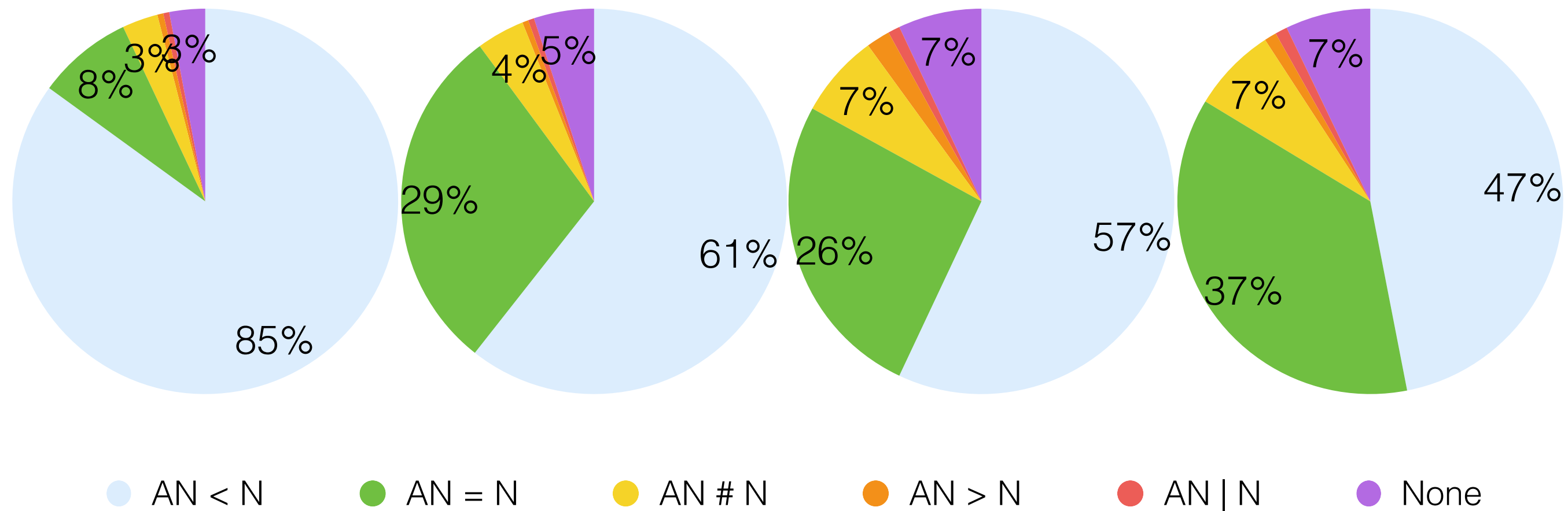
Up to 53% error rate by assuming all adjectives are restrictive.

Image Captions

Literature

News

Forums

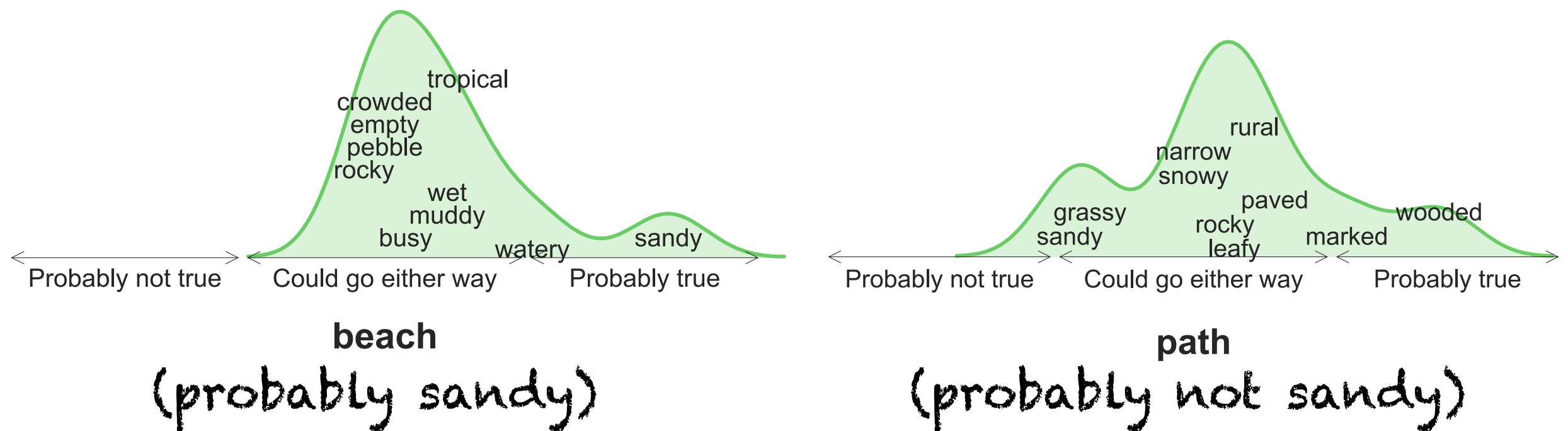


# When does N entail AN?



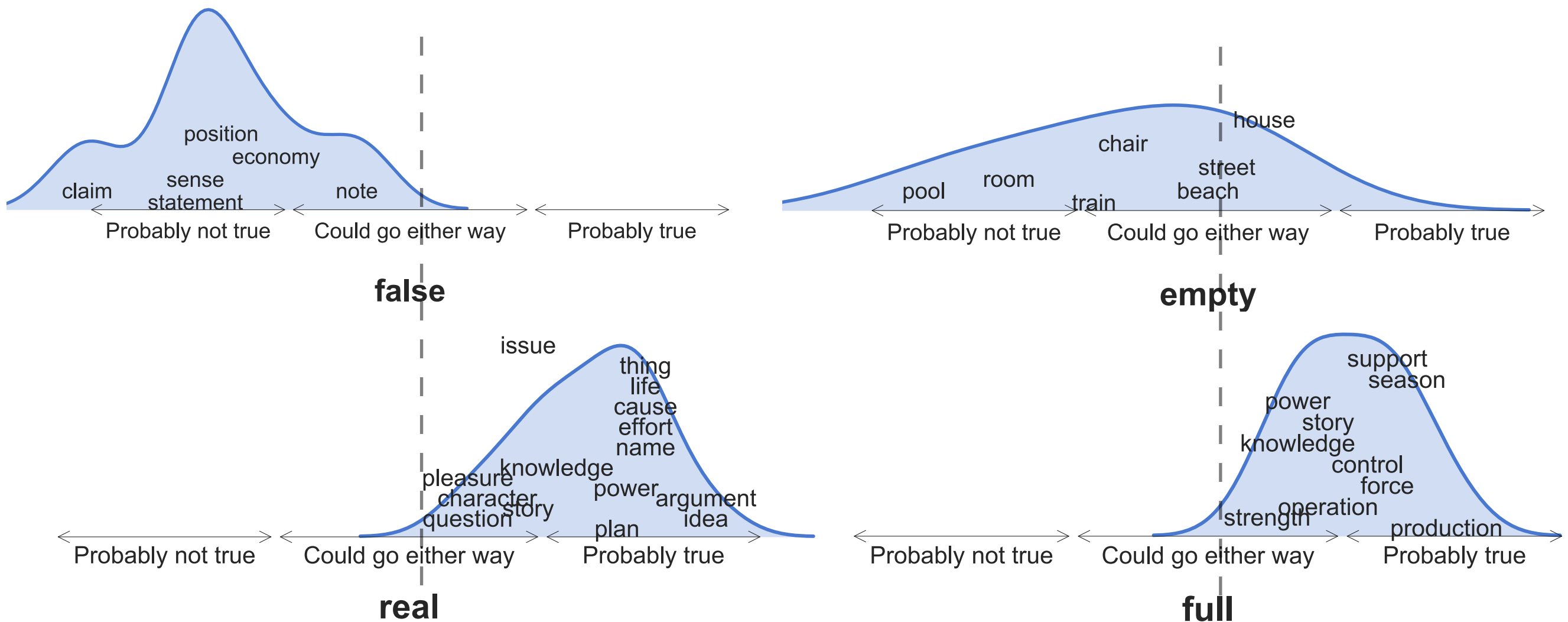
# When does N entail AN?

Sometimes, it is a property of the adjective and noun...



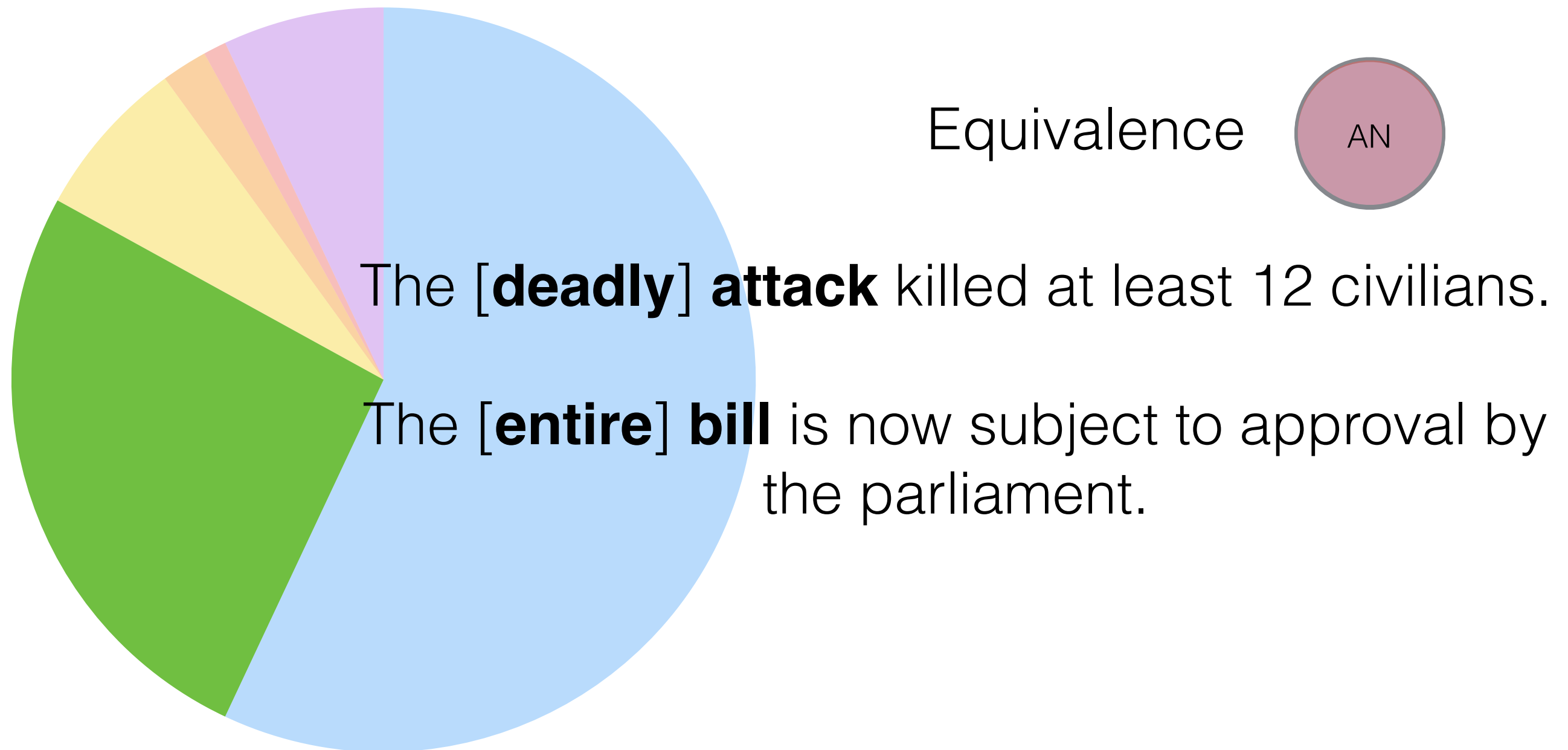
# When does N entail AN?

...or even just the adjective.



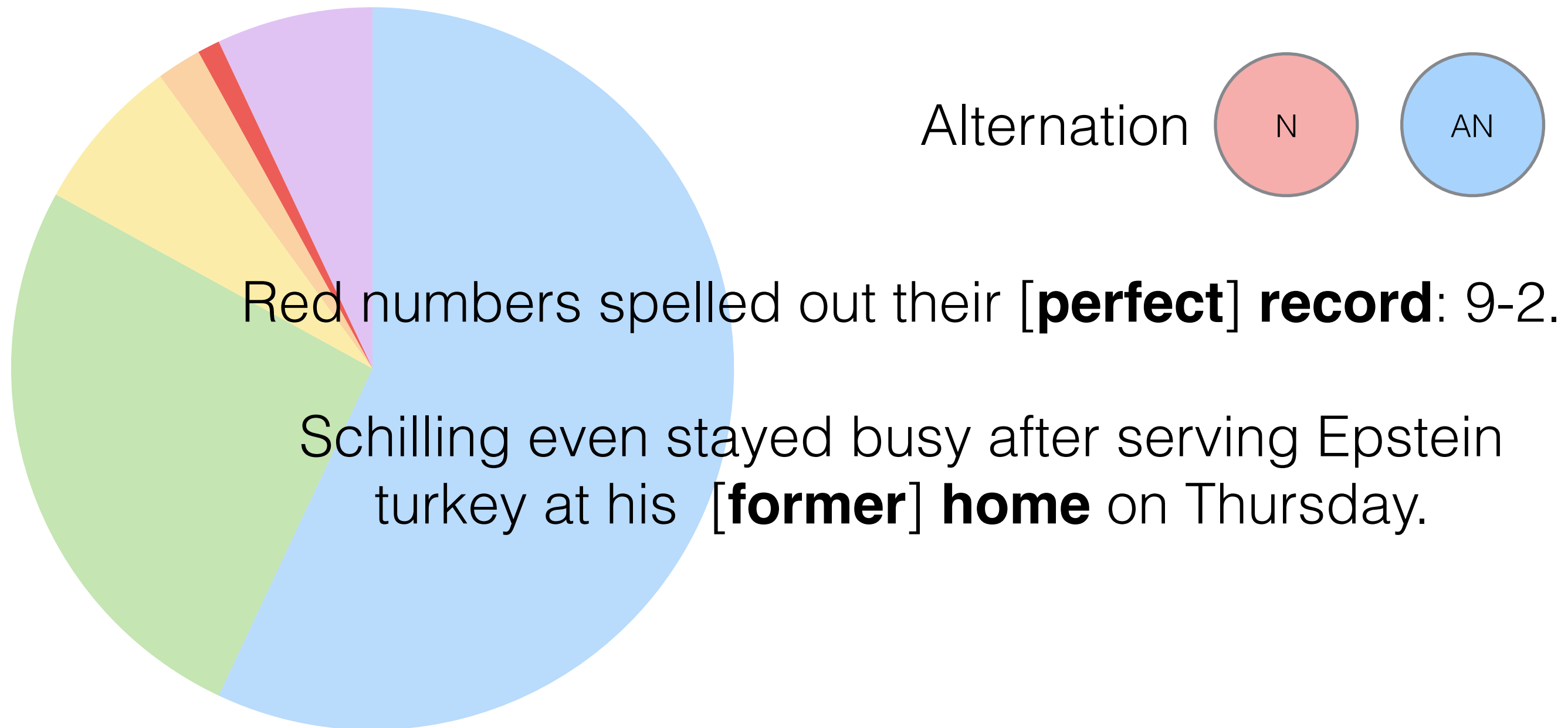
# When does N entail AN?

Other times, it is a property of the context+word knowledge.



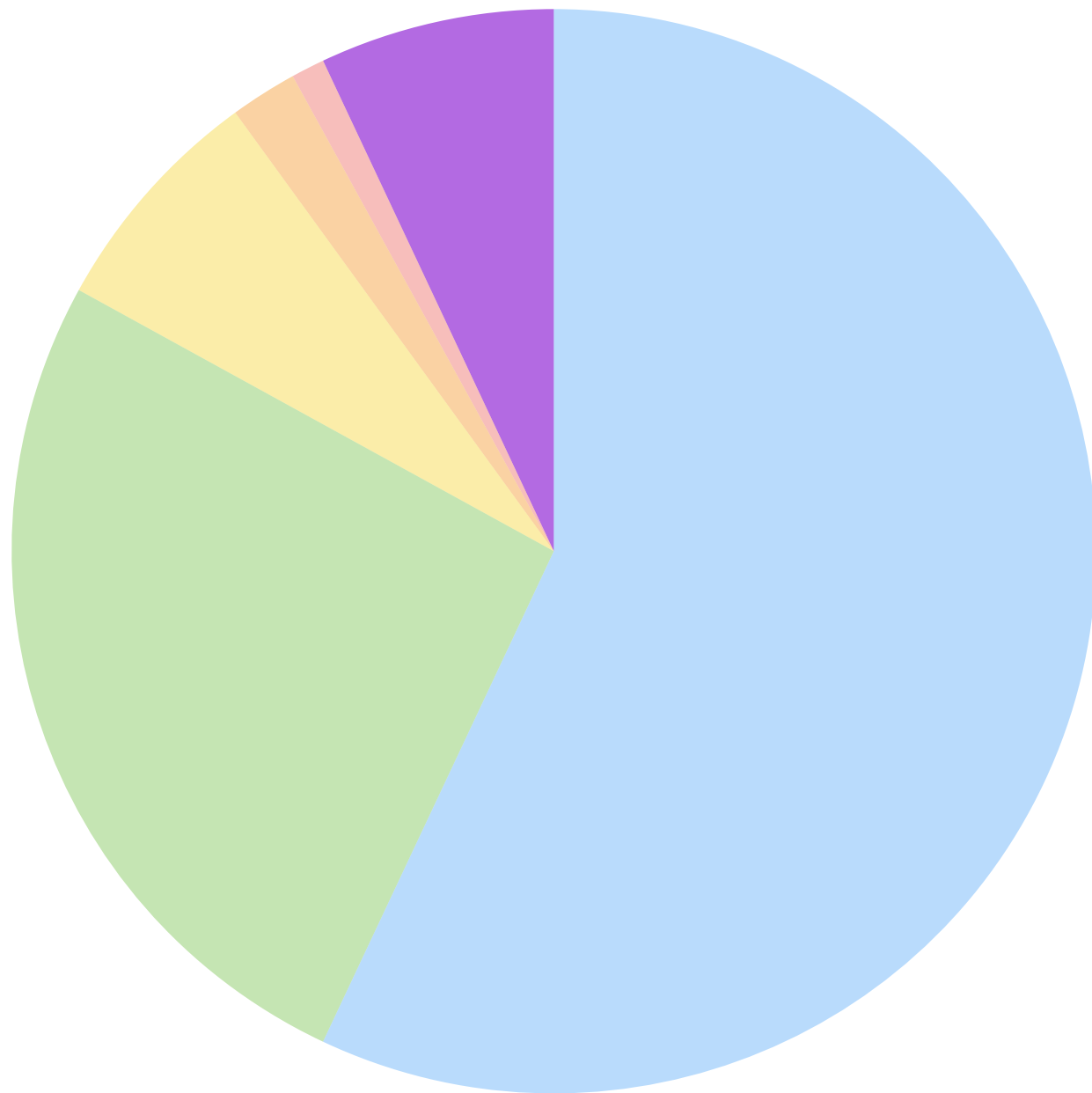
# When does N <sup>NOT</sup> entail AN?

Other times, it is a property of the context+word knowledge.



# When does N<sup>not</sup> entail AN?

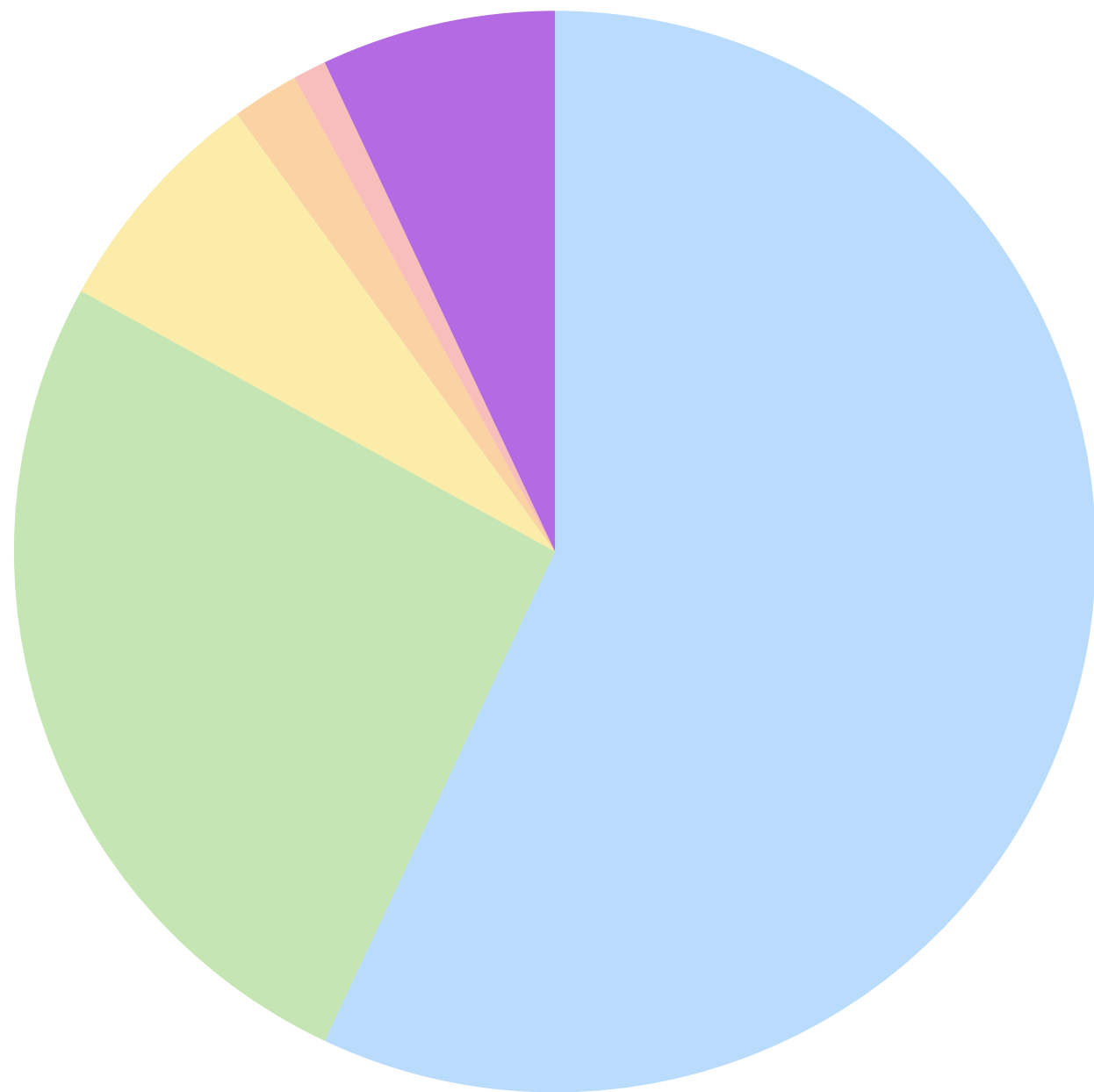
Other times, it is a property of the context+word knowledge.



Undefined Relations

# When does N <sup>NOT</sup> entail AN?

Other times, it is a property of the context+word knowledge.

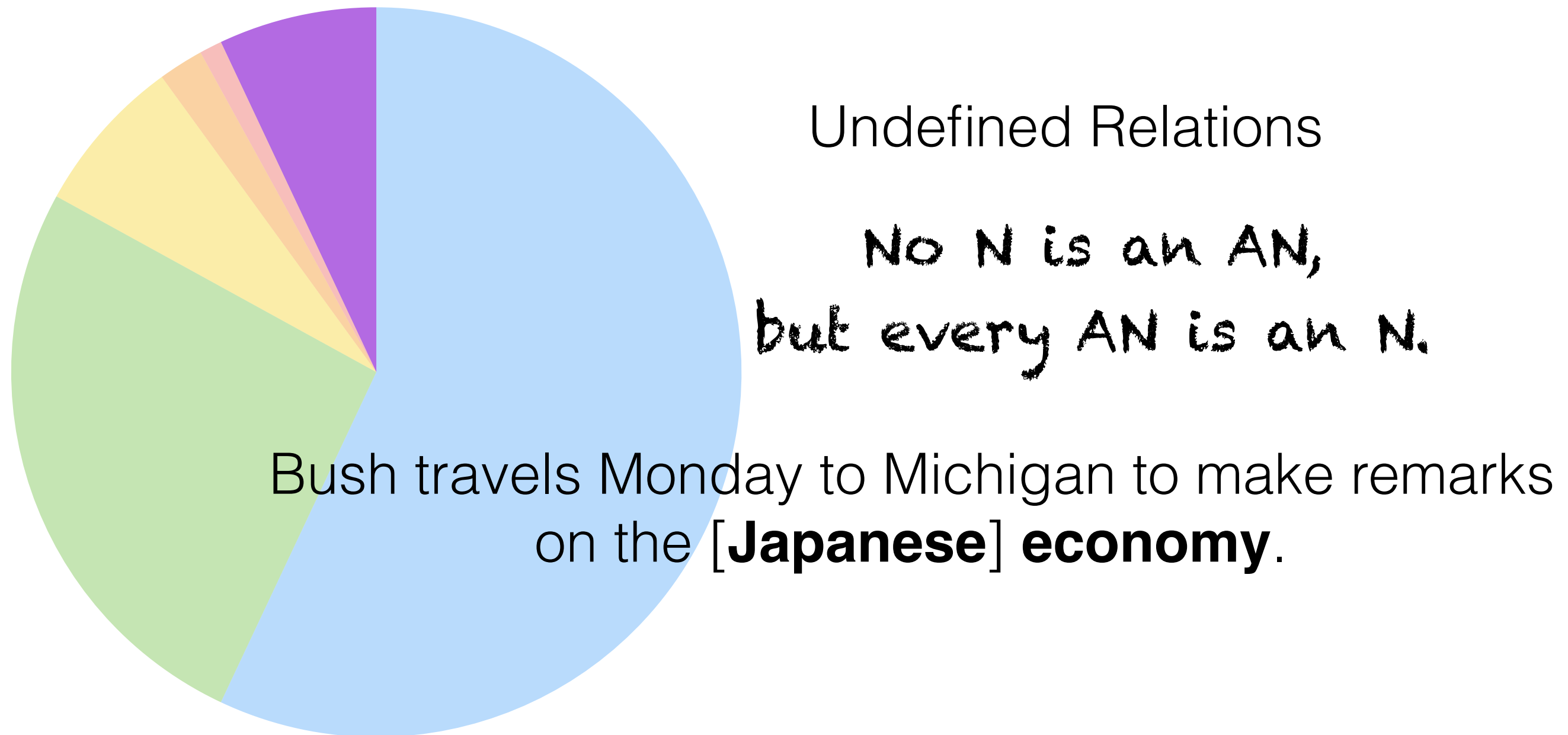


Undefined Relations

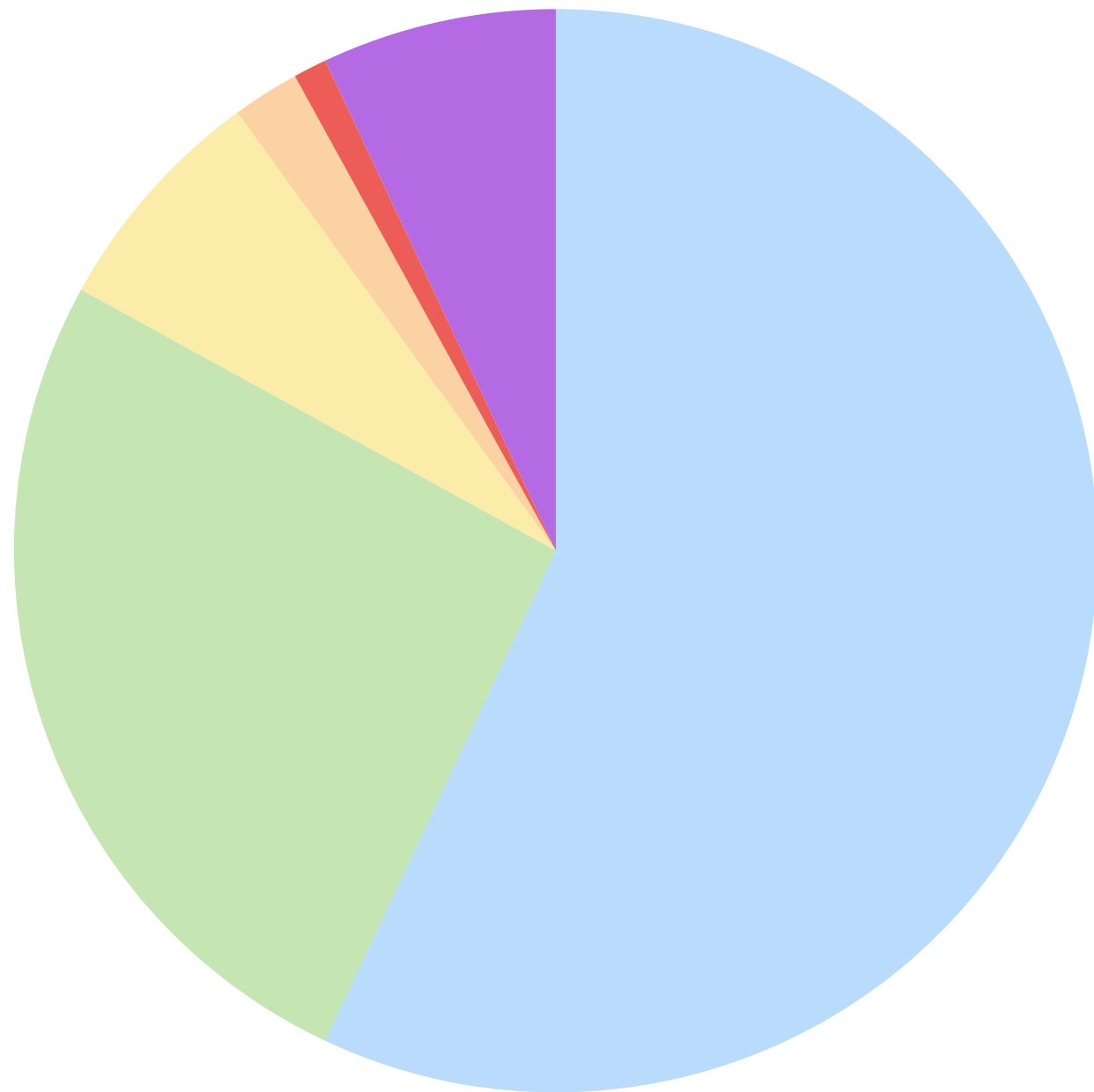
No N is an AN,  
but every AN is an N.

# When does N <sup>NOT</sup> entail AN?

Other times, it is a property of the context+word knowledge.



# When ~~does~~ <sup>should NOT</sup> N entail AN?



fake  
former  
artificial  
counterfeit  
possible  
probable  
unlikely  
likely  
...



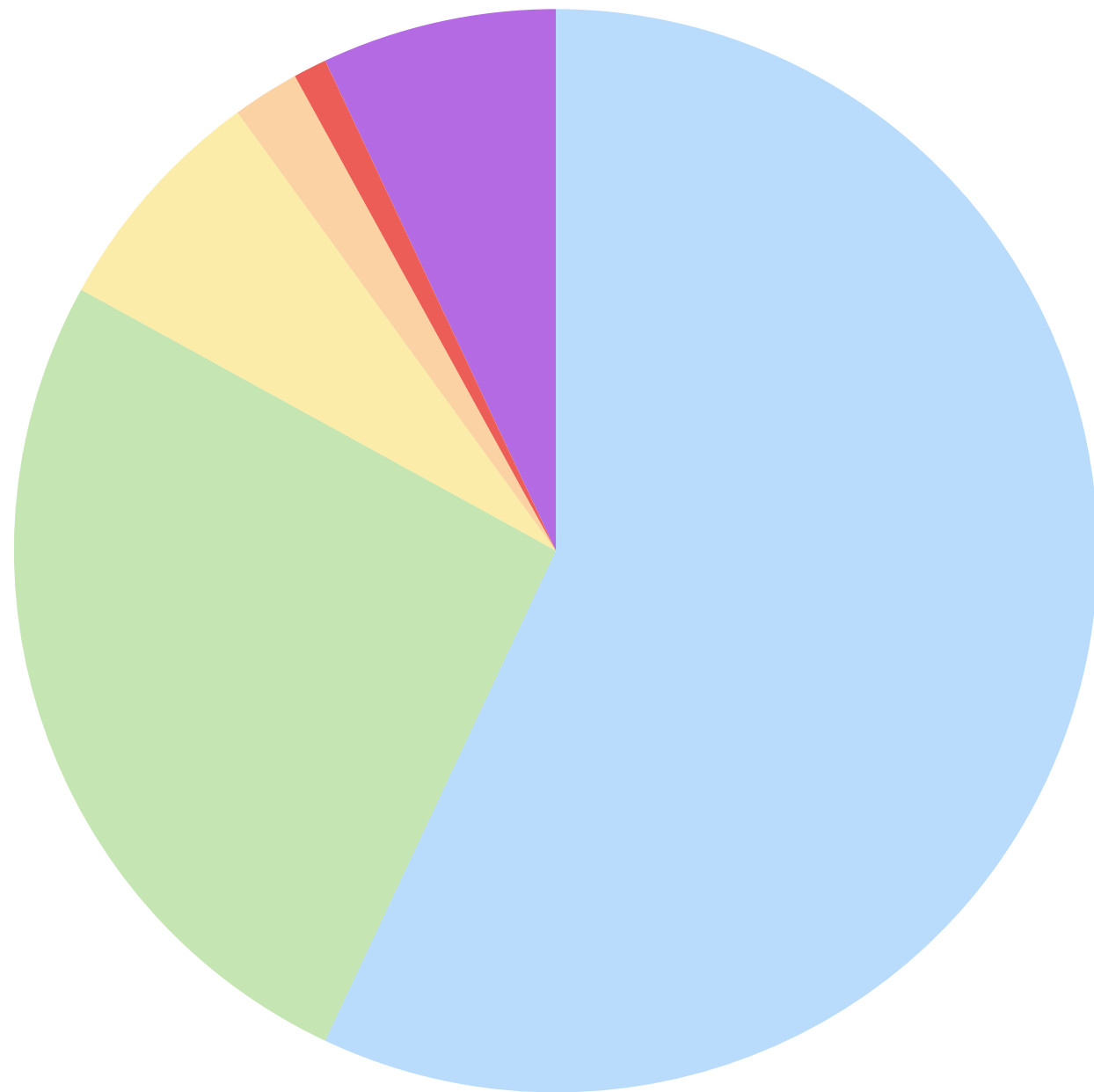
# DEL(**possible**)

Last December they had argued that the council had failed to consider **possible** effects of contaminated land at the site.

The council considered environmental consequences.

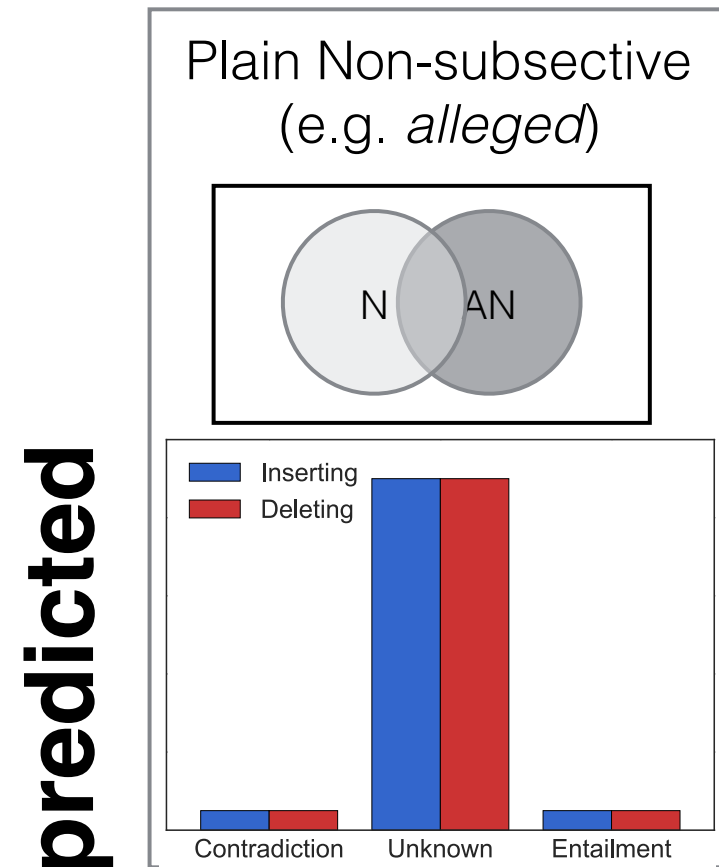
## **(non-subsective) modifiers**

# When ~~does~~ <sup>should NOT</sup> N entail AN?



fake  
former  
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counterfeit  
possible  
probable  
unlikely  
likely  
...

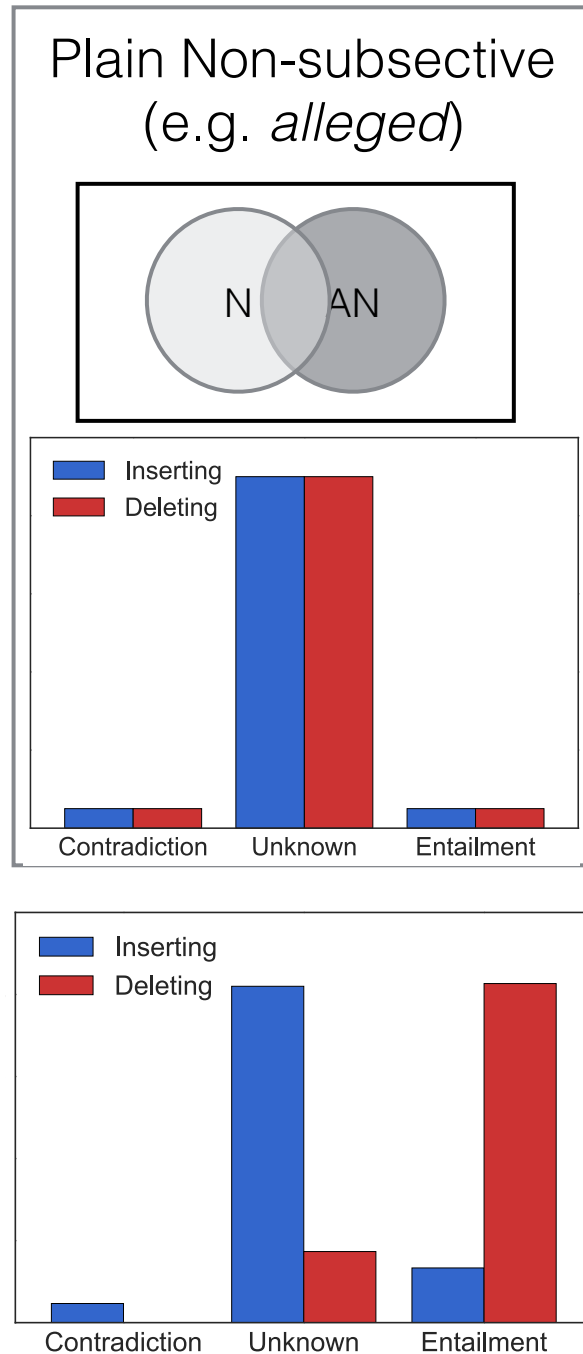
# When ~~does~~ <sup>should NOT</sup> N entail AN?



She was the **expected winner**.  
She was the **winner**.

# When ~~does~~ <sup>should NOT</sup> N entail AN?

predicted  
observed

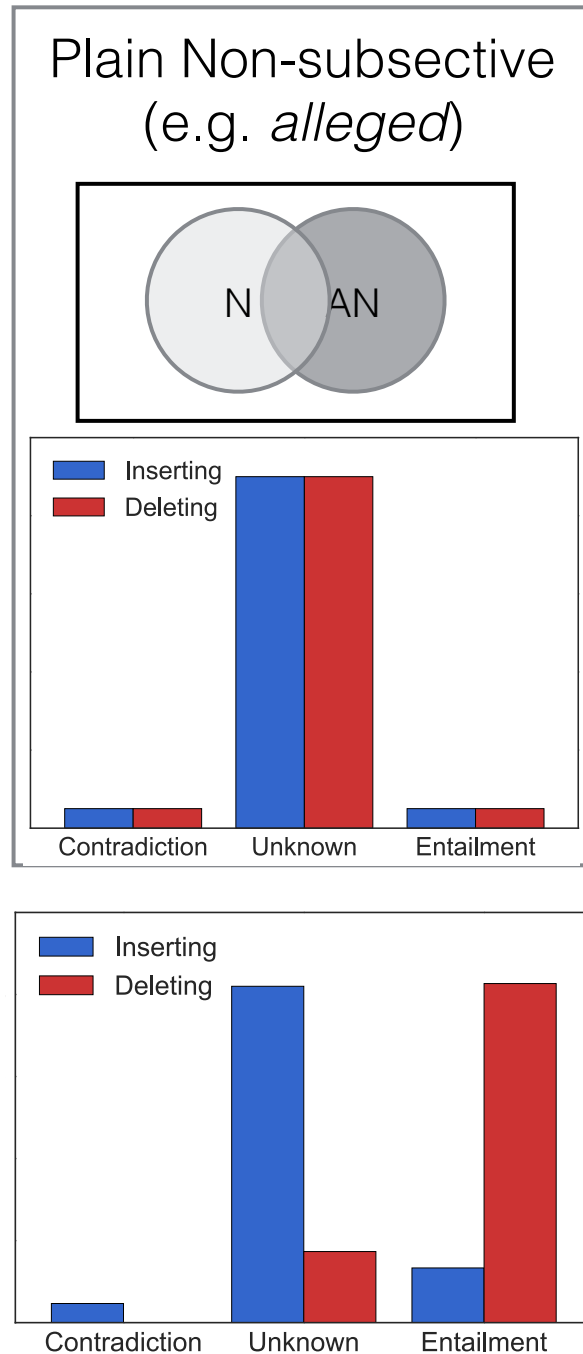


She was the **expected winner**.  
She was the **winner**.

Actually behave like normal,  
subjective adjectives (e.g. red).

# When ~~does~~ <sup>should NOT</sup> N entail AN?

predicted  
observed



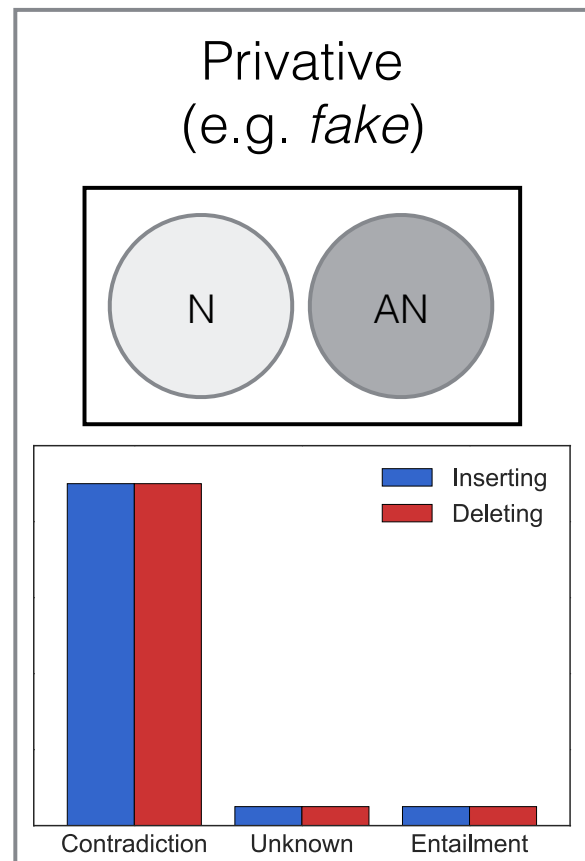
She was the **expected winner**.  
She was the **winner**.

Actually behave like normal,  
subjective adjectives (e.g. red).

To deal with an **expected surge** in  
unemployment, the plan includes a huge  
temporary jobs program.

# When ~~does~~ <sup>should NOT</sup> N entail AN?

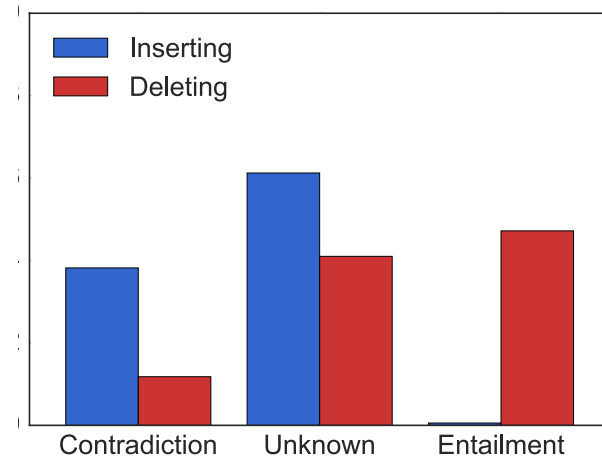
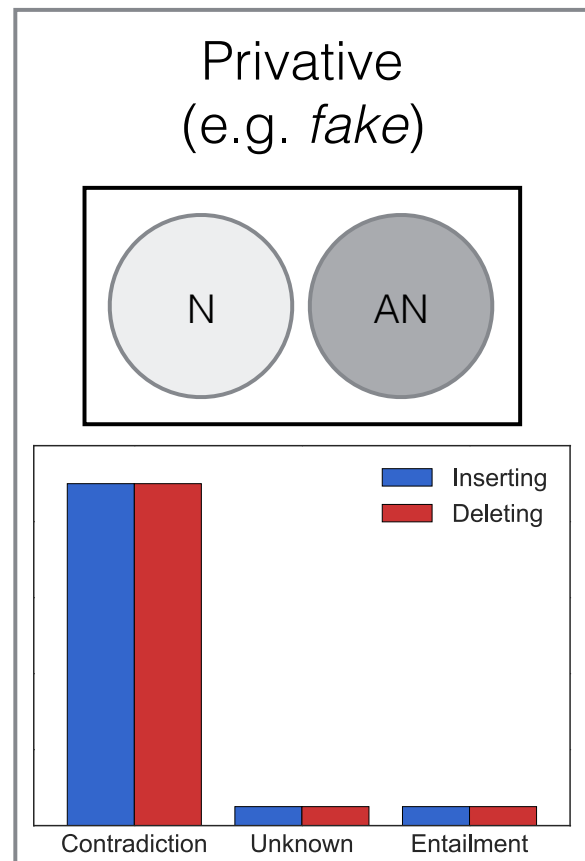
predicted



She was carrying a **fake gun**.  
She was carrying a **gun**.

# When ~~does~~ <sup>should NOT</sup> N entail AN?

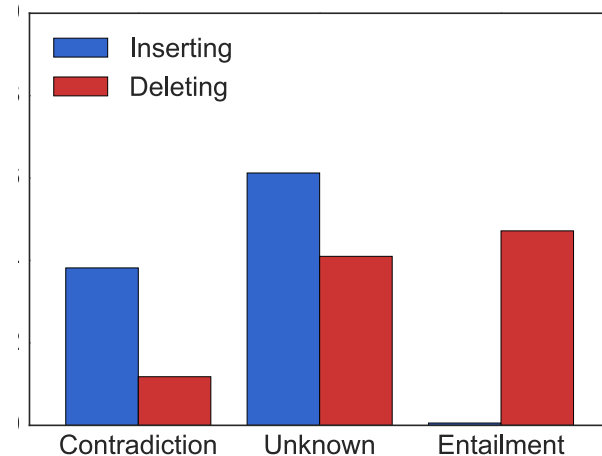
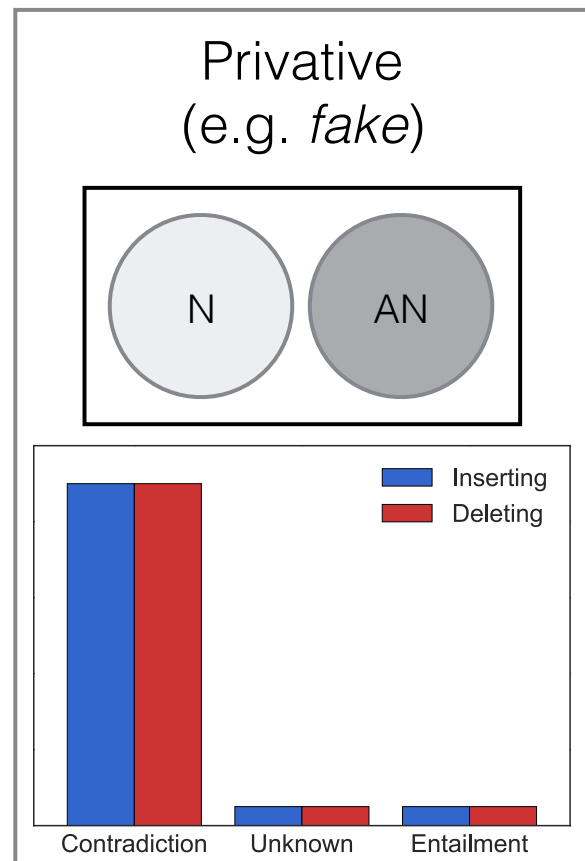
predicted  
observed



(a) Privative

# When <sup>should NOT</sup> ~~does~~ N entail AN?

predicted  
observed



(a) Privative

She was carrying a **fake gun**.  
She was carrying a **gun**.

Don't behave symmetrically.

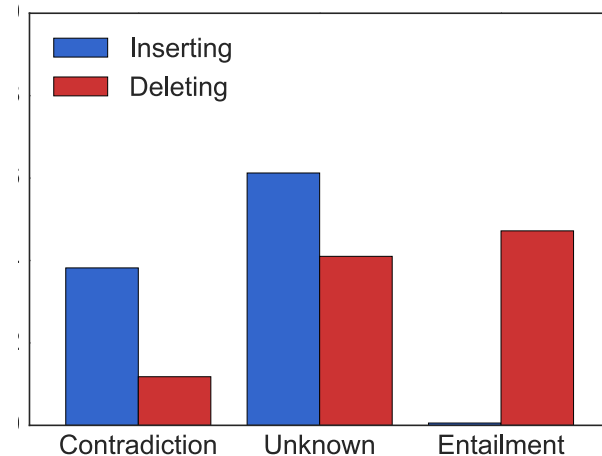
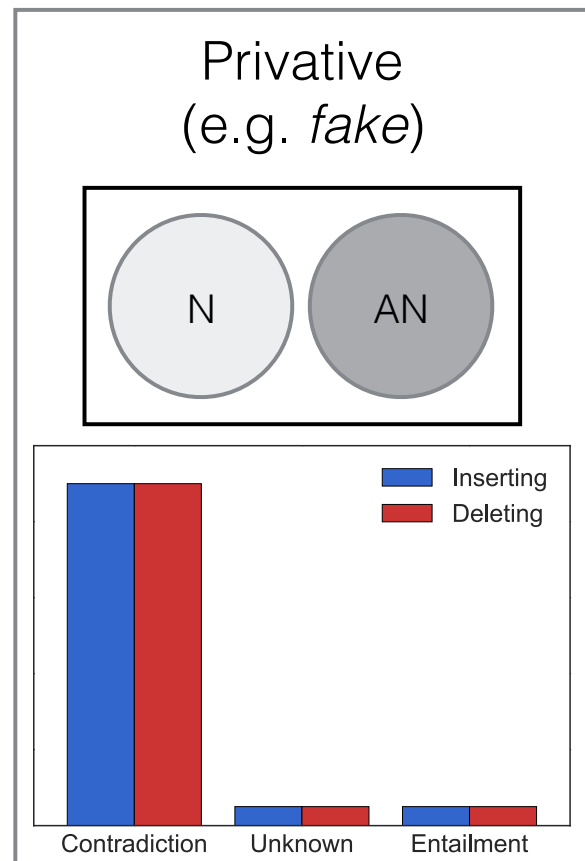
The 27-year-old Gazan seeks an **id** to get through security checkpoints and find work in Cairo.

Does he seek a **fake id**?



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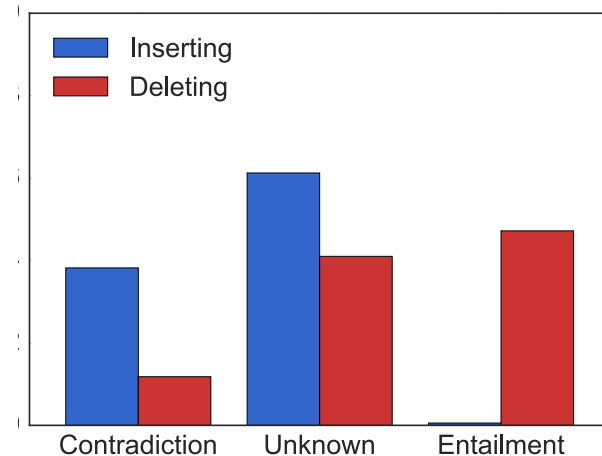
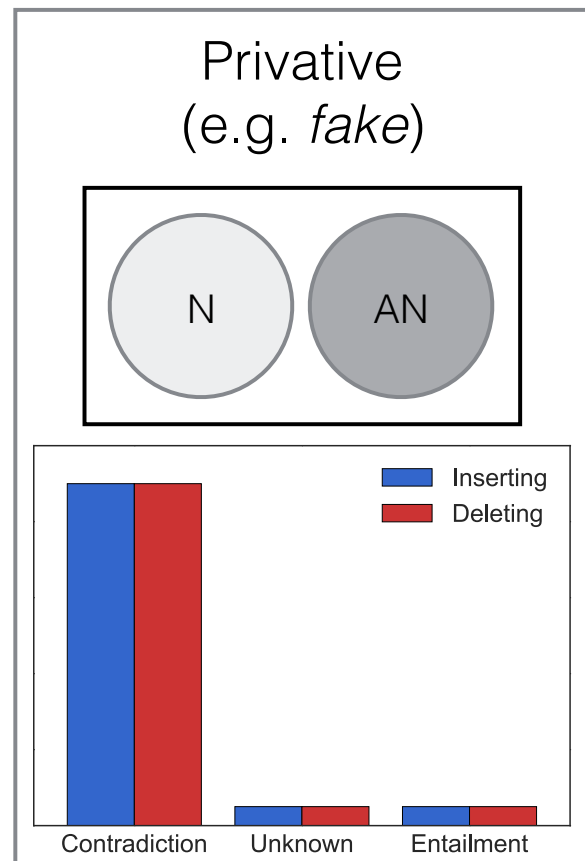
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She was carrying a **fake gun**.  
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Don't behave symmetrically.

The 27-year-old Gazan seeks a **fake id**  
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and find work in Cairo.

Does he seek a **id**?



# Does N entail AN?

Bush travels Monday to Michigan to make remarks  
on the **economy**.

# Does N entail AN?

Bush travels Monday to Michigan to make remarks  
on the **economy**.



Bush travels Monday to Michigan to make remarks  
on the **American economy**.

# Does N entail AN?

Bush travels Monday to Michigan to make remarks  
on the **economy**.



Bush travels Monday to Michigan to make remarks  
on the **American economy**.



Bush travels Monday to Michigan to make remarks  
on the **Japanese economy**.

# Does N entail AN?

Bush travels Monday to Michigan to make remarks  
on the **economy**.

5,378 naturally-occurring sentences  
4,868 train / 510 test

✓ Bush travels Monday to Michigan to make remarks  
on the **American economy**.

✗ Bush travels Monday to Michigan to make remarks  
on the **Japanese economy**.

# Does N entail AN?

Bush travels Monday to Michigan to make remarks  
on the **economy**.

5,378 naturally-occurring sentences  
4,868 train / 510 test

2,990 unique ANs  
Disjoint ANs in train/test

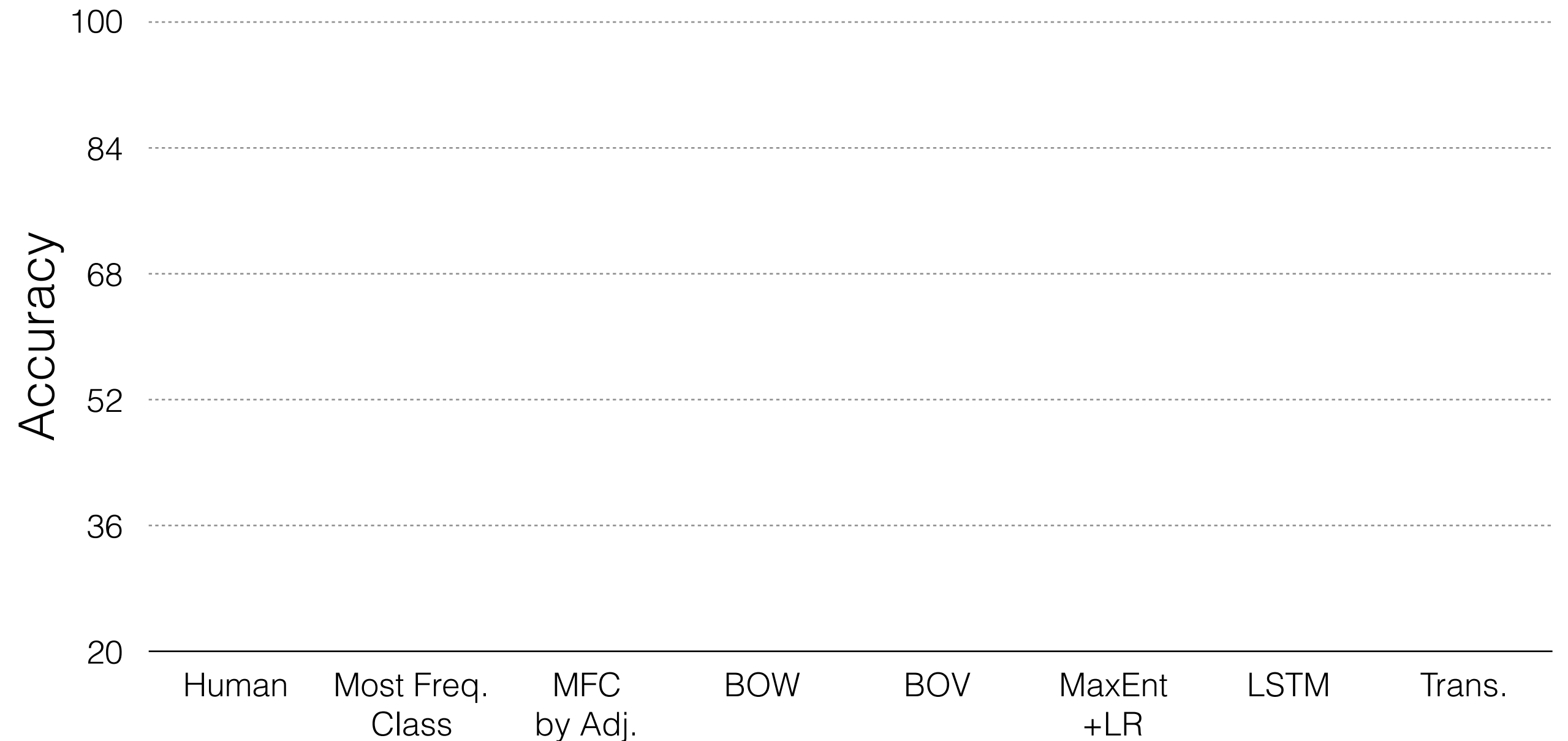


Bush travels Monday to Michigan to make remarks  
on the **American economy**.



Bush travels Monday to Michigan to make remarks  
on the **Japanese economy**.

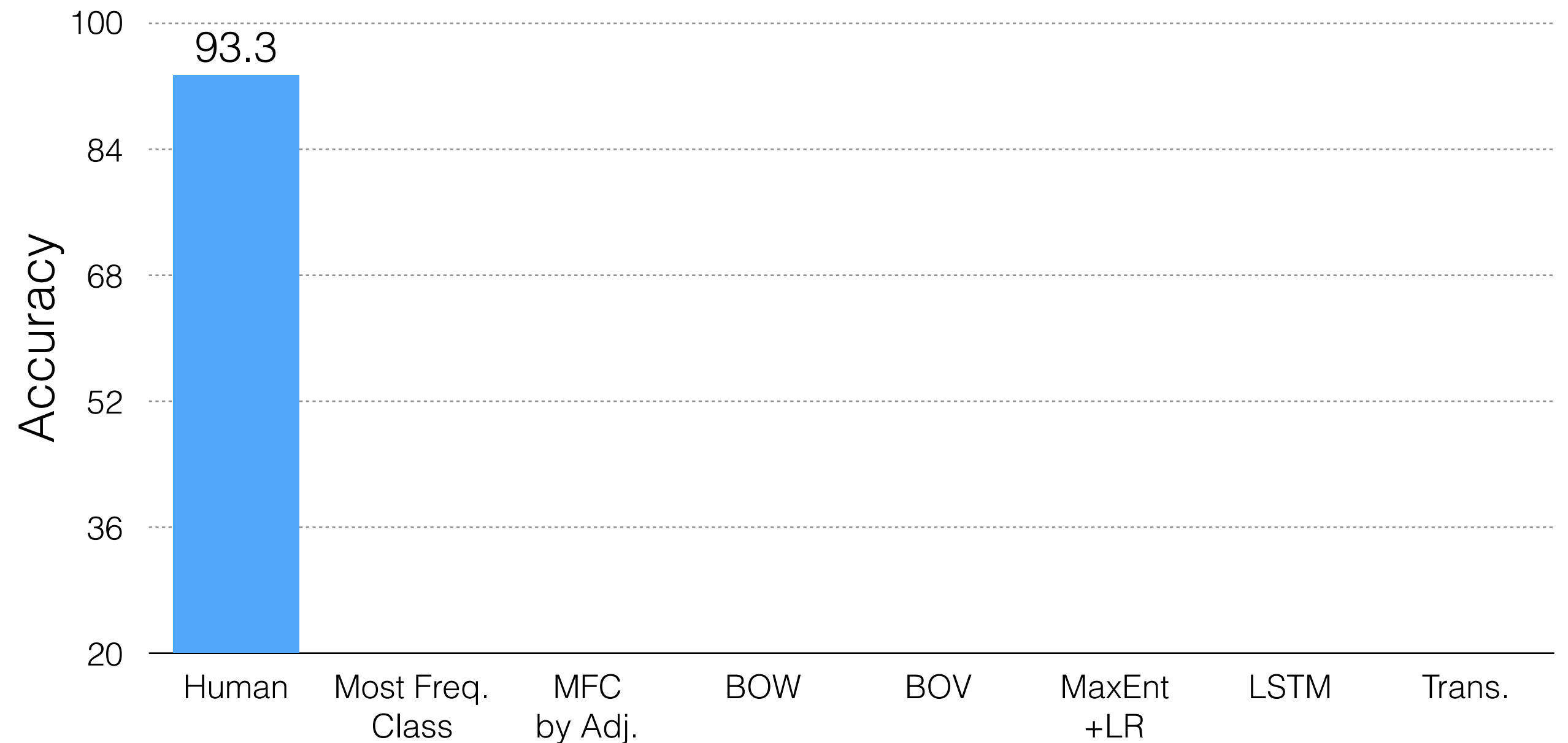
# Does N entail AN?



*Compositional Entailment in Adjective Nouns. (Pavlick and Callison-Burch ACL 2016)*

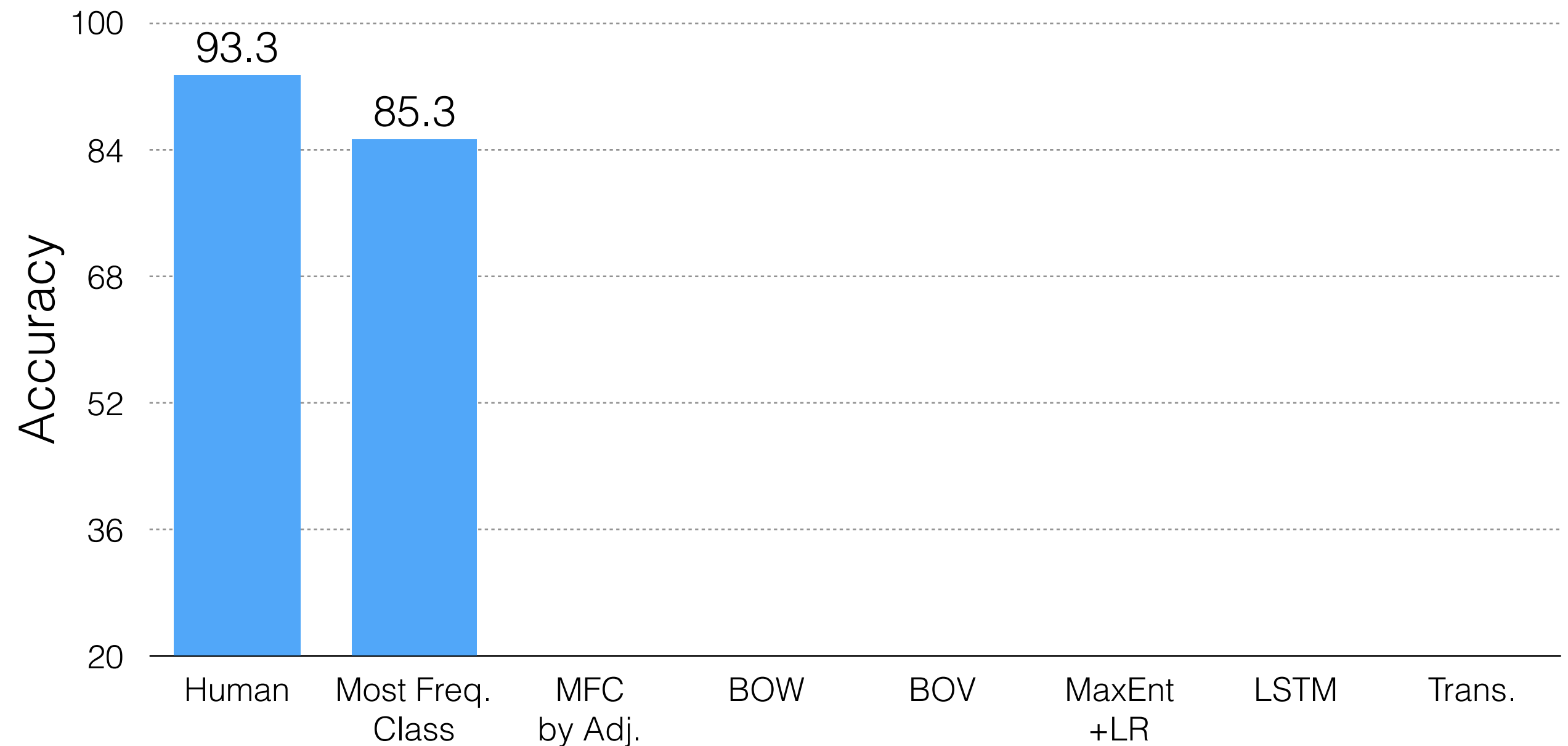


# Does N entail AN?



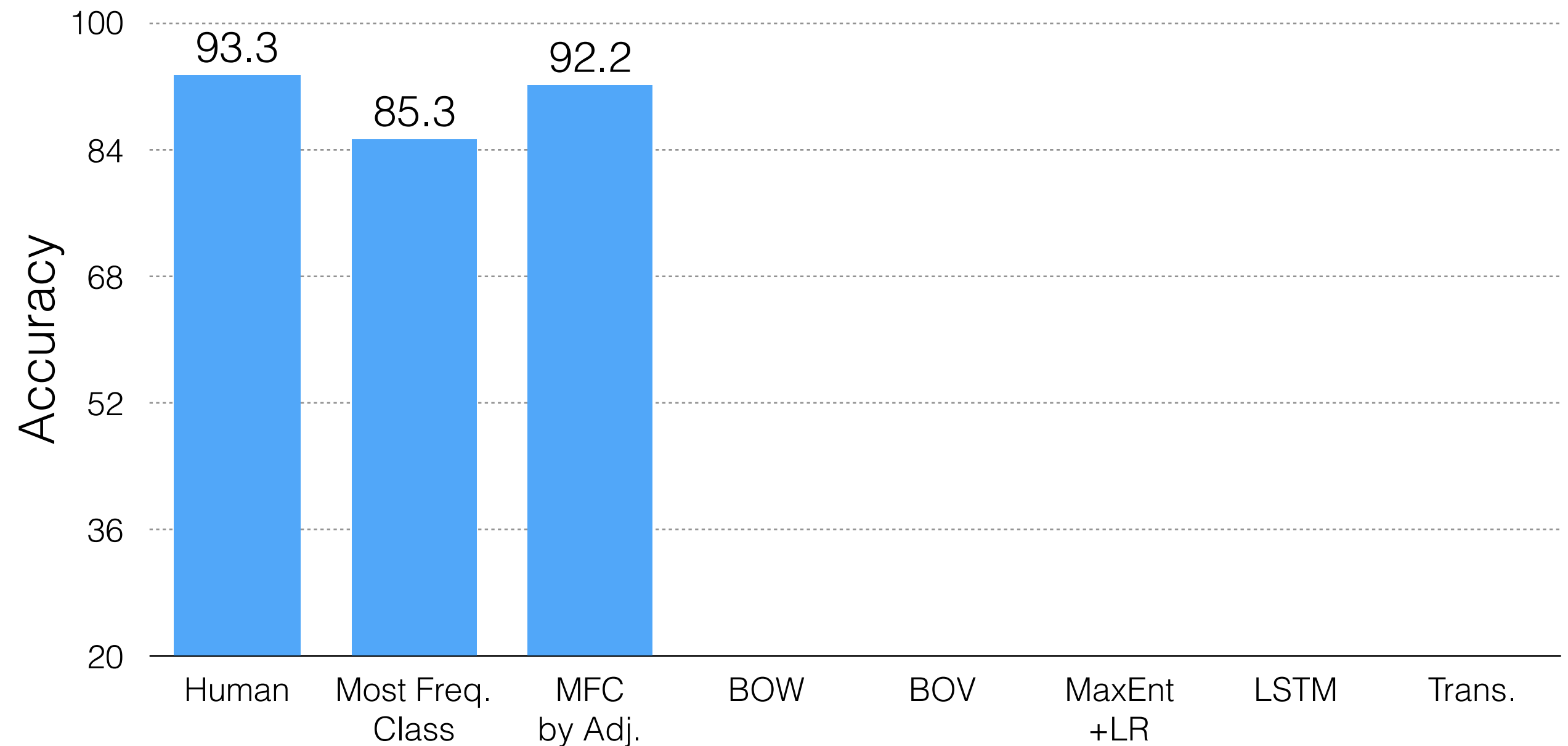
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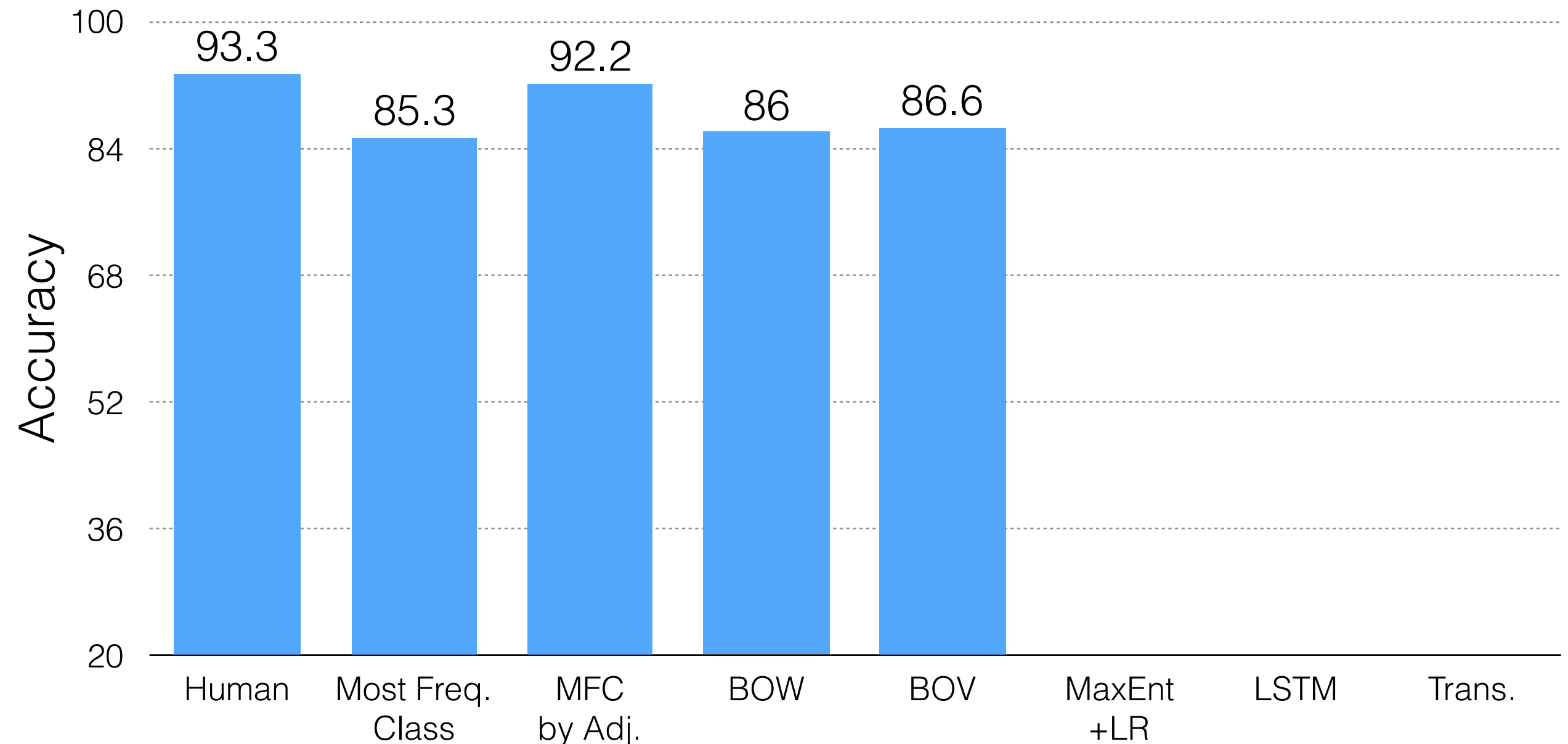
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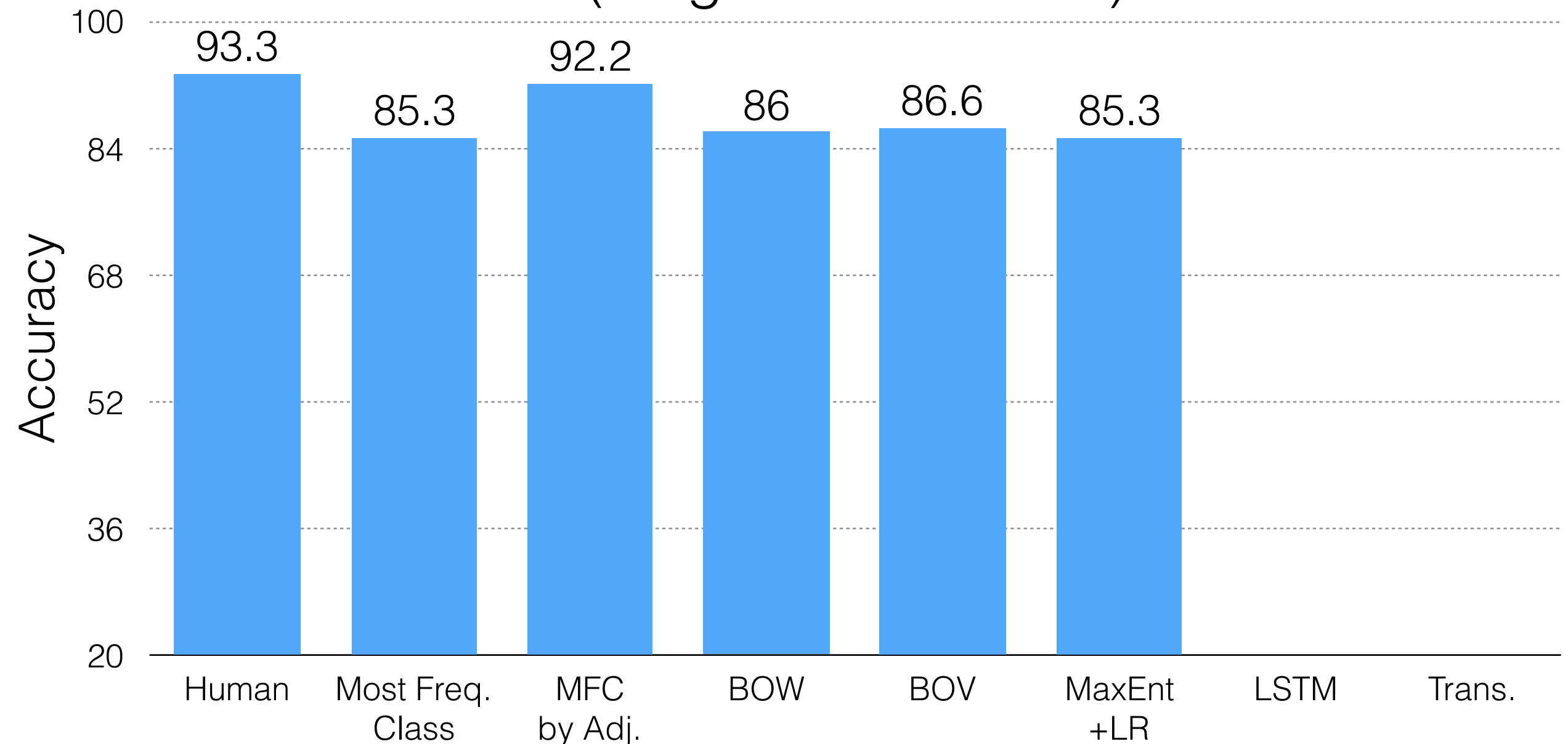
# Does N entail AN?

Pretty strong baselines



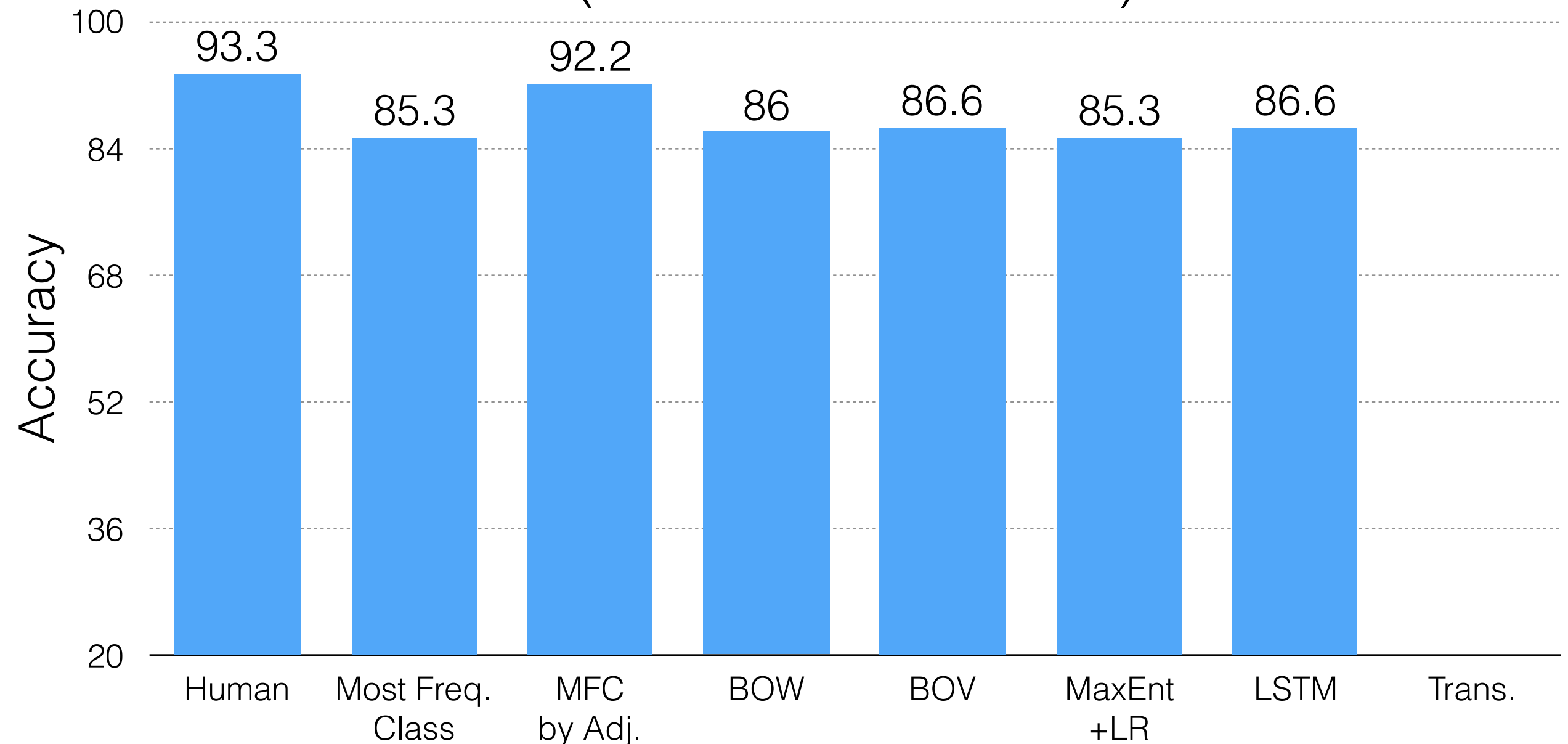
# Does N entail AN?

Supervised Model using involved NLP pipeline  
(Magnini et al. 2014)



# Does N entail AN?

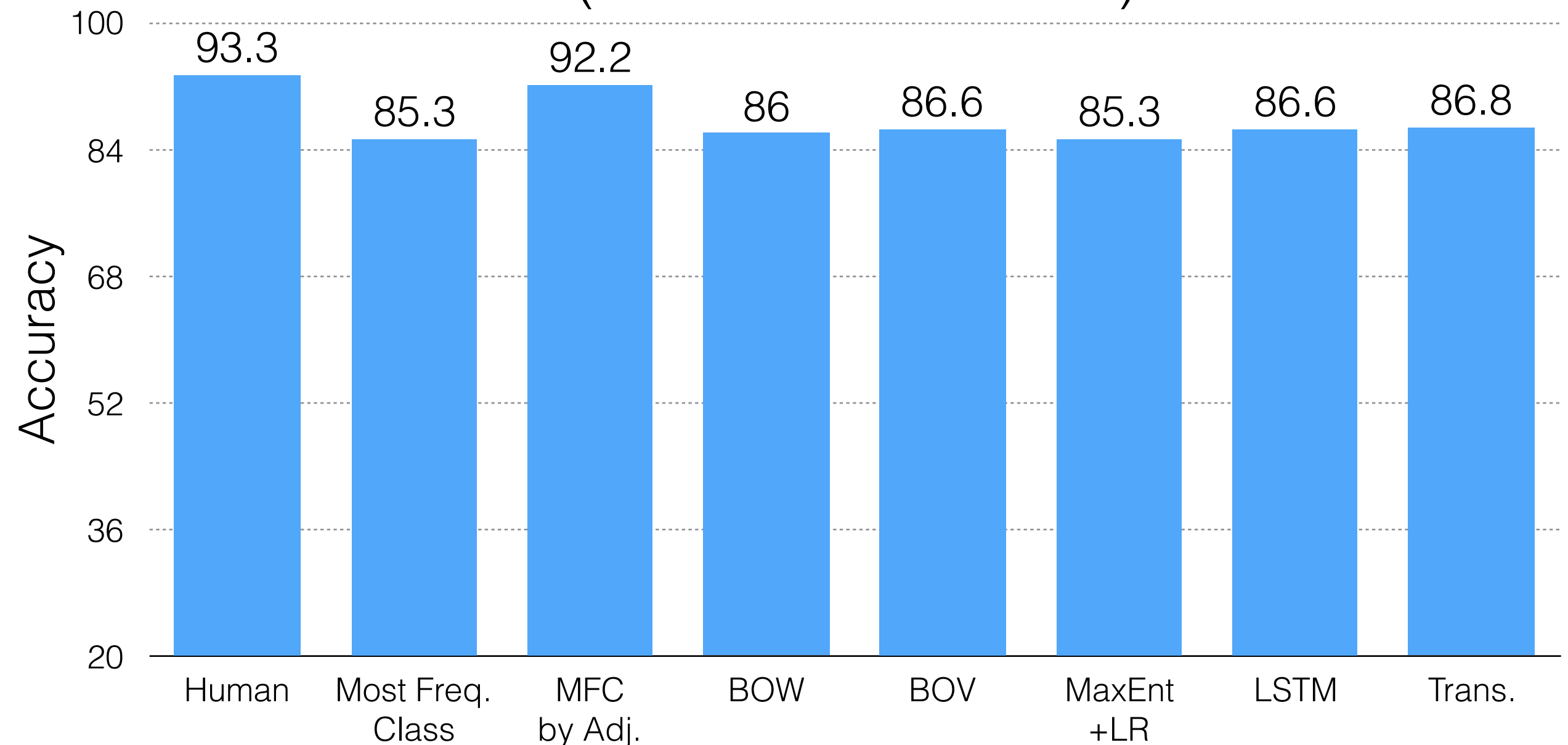
Several DNN Models  
(Bowman et al. 2015)



*Compositional Entailment in Adjective Nouns. (Pavlick and Callison-Burch ACL 2016)*

# Does N entail AN?

Several DNN Models, with transfer learning  
(Bowman et al. 2015)



*Compositional Entailment in Adjective Nouns. (Pavlick and Callison-Burch ACL 2016)*

# Summary



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- Humans are **flexible** with their language, they don't abide by hard-and-fast logical rules of composition and entailment.

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- ...but lexical entailments are not enough. We need **composition** in order to model unseen phrases and full sentences.

# Summary

- Humans are **flexible** with their language, they don't abide by hard-and-fast logical rules of composition and entailment.
- We can **acquire lexical entailments at scale**...
- ...but lexical entailments are not enough. We need **composition** in order to model unseen phrases and full sentences.
- Inference involving composition is **too complex to capture using simple heuristics**, and requires models to incorporate **context and common sense** when performing reasoning.

# Current Work

# SUB(**consider**, **consider**)

Last December they had argued that the council had failed to **consider** possible effects of contaminated land at the site.

The council **considered** environmental consequences.

## **predicates**

# Projection through Predicates

		Input	Output
in France $\sqsubseteq$ in Europe	Forward		
in Europe $\sqsupseteq$ in France	Reverse		
in France   in Germany	Alternation		
in France # in the city	Independent		

*Current Work-in-progress.*

# Projection through Predicates

		Input	Output
in France $\sqsubseteq$ in Europe	Forward		
in Europe $\sqsupseteq$ in France	Reverse		
in France   in Germany	Alternation		
in France # in the city	Independent		

**born**

*Current Work-in-progress.*




# Projection through Predicates

		Input	Output
in France $\sqsubseteq$ in Europe	Forward		
in Europe $\supseteq$ in France	Reverse		
in France   in Germany	Alternation		
in France # in the city	Independent		

**born**(in France)  $\sqsubseteq$  **born**(in Europe)

*Current Work-in-progress.*


# Projection through Predicates

		Input	Output
in France $\sqsubseteq$ in Europe	Forward		
in Europe $\supseteq$ in France	Reverse		
in France   in Germany	Alternation		
in France # in the city	Independent		

**born**(in Europe)  $\supseteq$  **born**(in France)

*Current Work-in-progress.*






# Projection through Predicates

		Input	Output
in France $\sqsubseteq$ in Europe	Forward		
in Europe $\sqsupseteq$ in France	Reverse		
in France   in Germany	Alternation		
in France # in the city	Independent		

**born**(in France) | **born**(in Germany)

*Current Work-in-progress.*

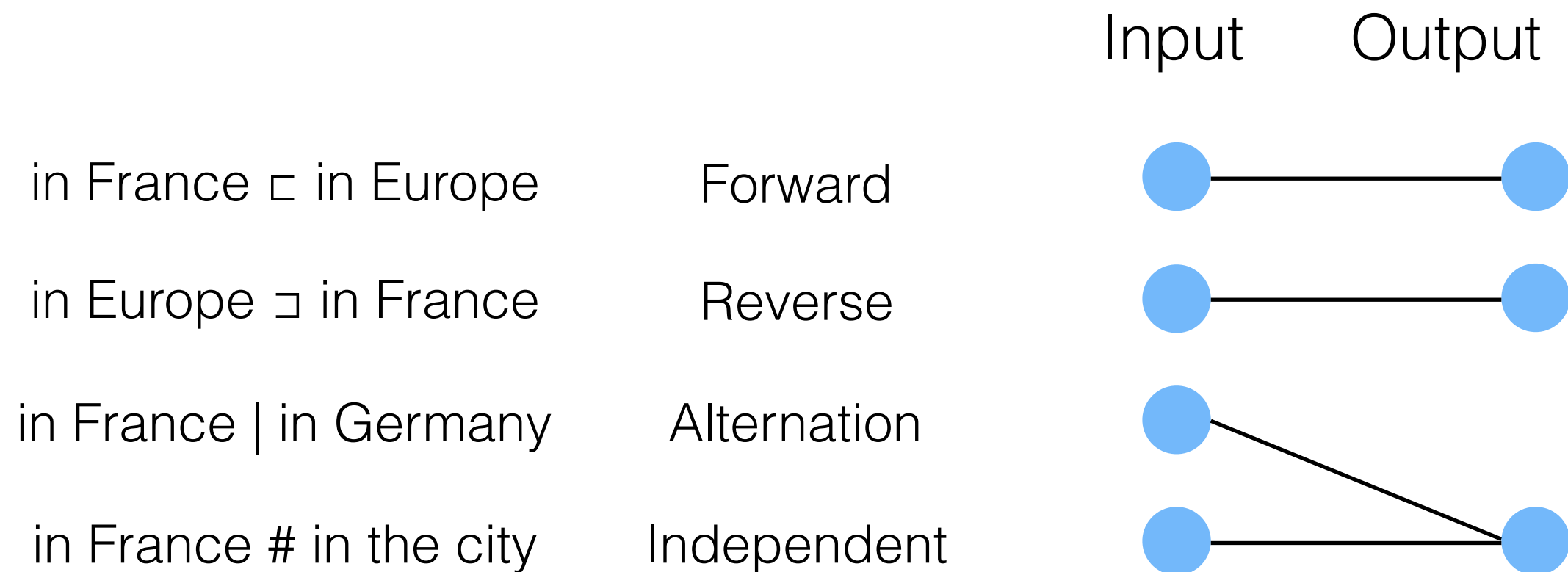
# Projection through Predicates

		Input	Output
in France $\sqsubseteq$ in Europe	Forward		
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in France # in the city	Independent		

**born**(in France) # **born**(in the city)

*Current Work-in-progress.*

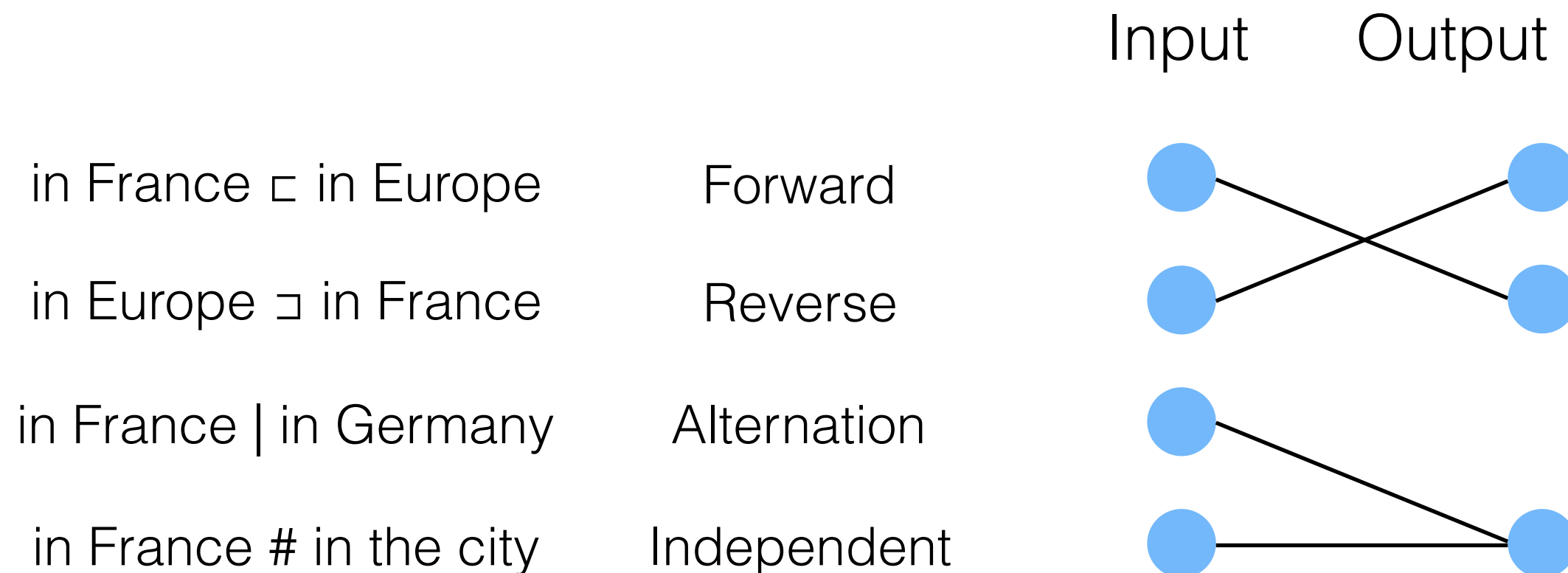
# Projection through Predicates



**has traveled**(in France)  
# **has traveled**(in Germany)

*Current Work-in-progress.*

# Projection through Predicates

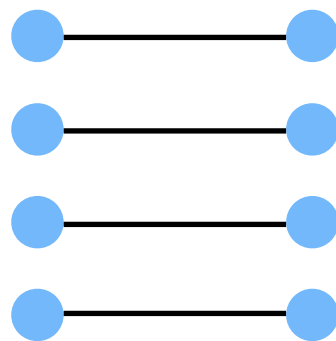


**is banned**(in France)  
 $\sqsubseteq$  **is banned**(in Europe)

*Current Work-in-progress.*

# Projection through Predicates

Identity



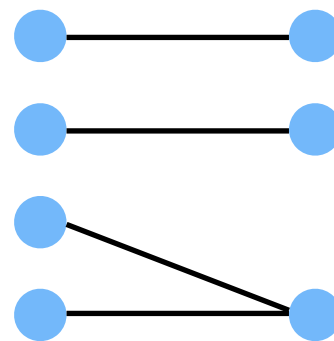
**is a**

**lives in**

**was born in**

**is married to**

Non-Exclusive,  
Identity



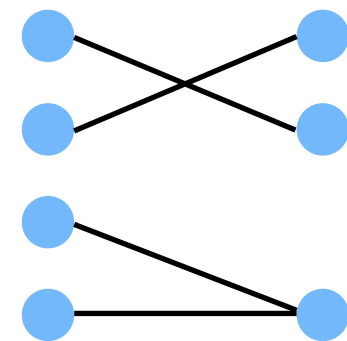
**has a**

**considers**

**has visited**

**likes**

Non-Exclusive,  
Negation



**lacks a**

**avoids**

**banned**

**dislikes**

# DEL(**fail to**)

Last December they had argued that the council had **failed to** consider possible effects of contaminated land at the site.

The council considered environmental consequences.

**“higher order”  
predicates**



# Implicative Verbs

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She **managed to** fix the bug.

# Implicative Verbs

She **managed to** fix the bug.

She **wanted to** fix the bug.

# Implicative Verbs

She **managed to** fix the bug.

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Did she fix the bug?

# Implicative Verbs

She **managed to** fix the bug. 

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Did she fix the bug?

# Implicative Verbs

She **managed to** fix the bug last night.

She **managed to** fix the bug tomorrow.

# Implicative Verbs

She **managed to** fix the bug last night. ✓

She **managed to** fix the bug tomorrow. ✗

# Implicative Verbs

She **wanted to** fix the bug last night. ✓

She **wanted to** fix the bug tomorrow. ✓



# Implicative Verbs

decide to

try to

intend to

venture to

get to

plan to

promise to

want to

bother to

forget to

agree to

dare to

manage to

happen to

hope to

# Implicative Verbs

venture to  
forget to  
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bother to  
happen to  
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dare to  
try to  
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promise to  
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intend to  
plan to  
hope to

# Implicative Verbs

Gallager **chose to**  
**accept** a full scholarship  
to play football for Temple  
University.

venture to  
forget to  
manage to  
bother to  
happen to  
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decide to  
dare to  
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hope to

# Implicative Verbs

Gallager **chose to accept** a full scholarship to play football for Temple University.

venture to  
forget to  
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bother to  
happen to  
get to  
decide to  
dare to  
try to  
agree to  
promise to  
want to  
intend to  
plan to  
hope to

Wilkins **was allowed to leave** in 1987 to join French outfit Paris Saint-Germain.

# Implicative Verbs

She **managed to** fix the bug.

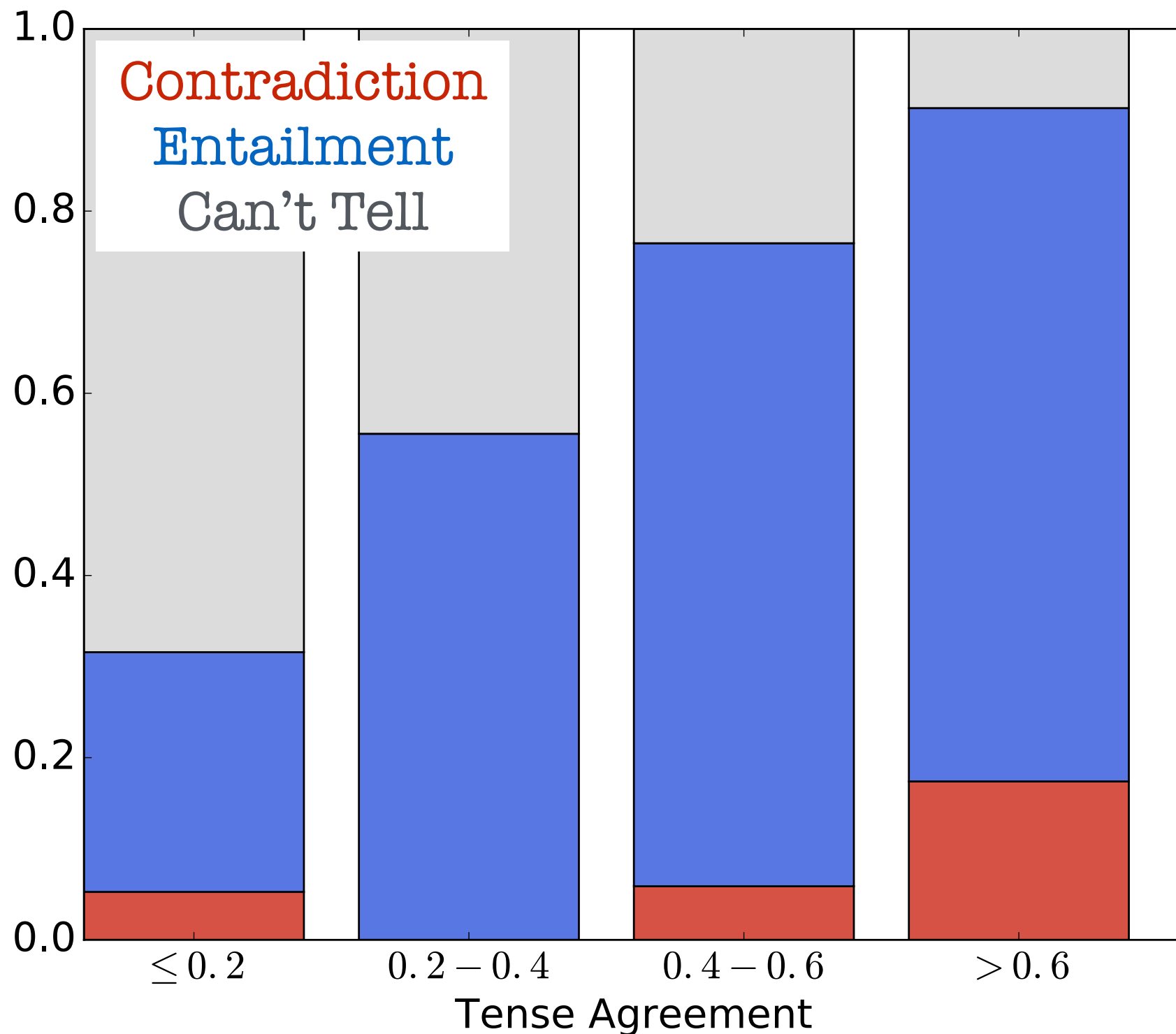
She fixed the bug.

Contradiction

Entailment

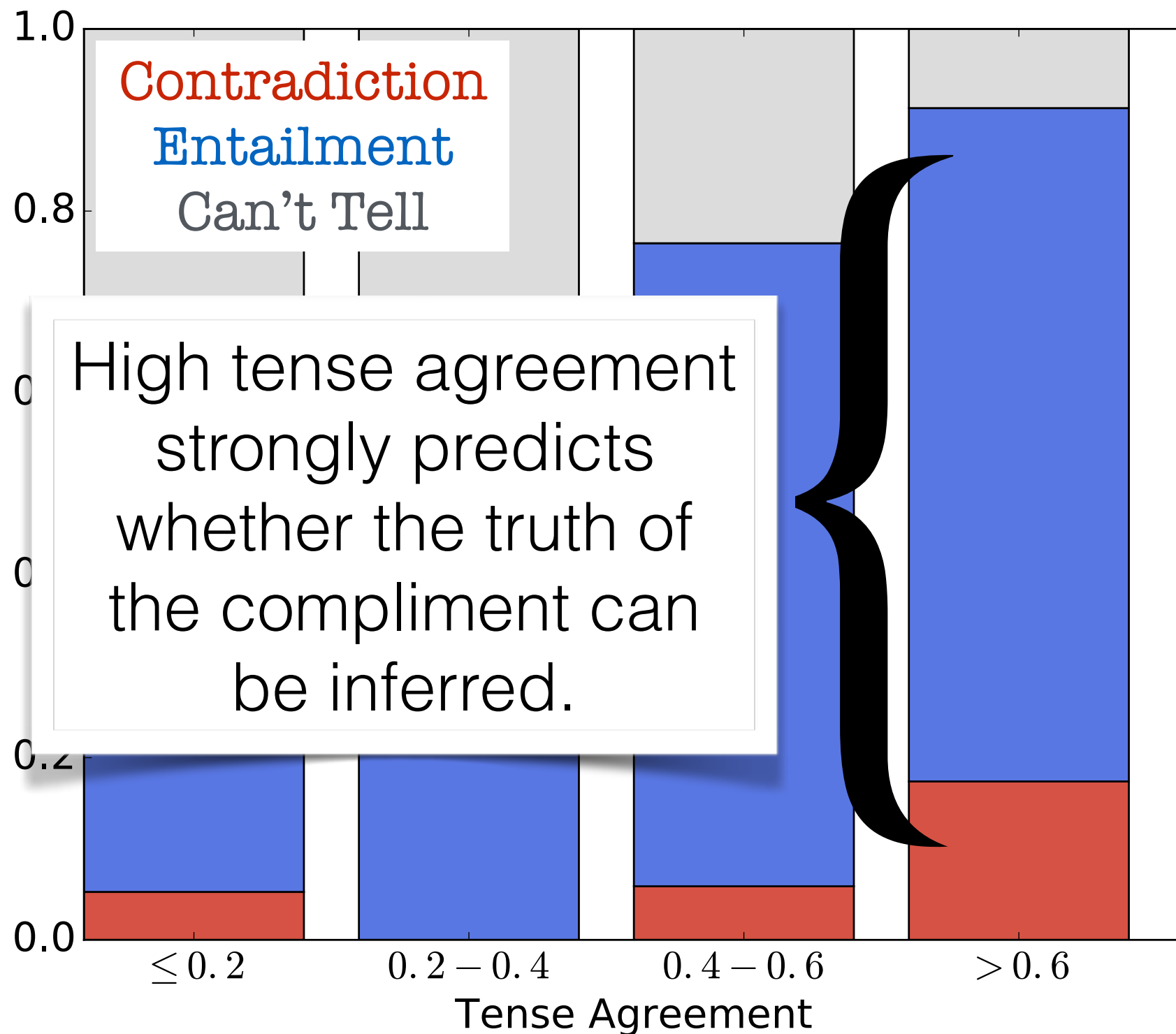
Can't Tell

# Implicative Verbs



*Tense Manages to Predict Implicatives. (Pavlick and Callison-Burch EMNLP 2016)*

# Implicative Verbs



# Discussion



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- Humans are flexible with their language.  
Computers need to be flexible too.

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# Discussion

- Humans are flexible with their language. Computers need to be flexible too.
- What aspects of meaning do we expect our semantic representations have built-in? What do we expect to have to deal with in context, at runtime?
- What types of semantic tasks should we need to optimize for explicitly? Shouldn't some things come "for free" when we train for harder tasks?

# Bibliography

Bannard and Callison-Burch. Paraphrasing with bilingual parallel corpora. ACL 2005.

Bos. Wide-coverage semantic analysis with boxer. STEP 2008.

Bowman et al. A large annotated corpus for learning natural language inference. EMNLP 2015.

Ganitkevitch et al. PPDB: The paraphrase database. NAACL 2013.

Hearst. Automatic acquisition of hyponyms from large text corpora. COLING 1992.

Karttunen. Implicative Verbs. Language 1971.

Lin and Pantel. Discovery of Inference Rules from Text. SIGKDD 2001.

MacCartney. Natural Language Inference. PhD Thesis 2009.

Padó et al. Design and realization of a modular architecture for textual entailment. NLE 2014.

Pavlick and Callison-Burch. Most babies are little and most problems are huge: Compositional Entailment in Adjective-Nouns. ACL 2016.

Pavlick and Callison-Burch. So-Called Non-Subsecutive Adjective.\*SEM 2016.

Pavlick and Callison-Burch. Tense Manages to Predict Implicative Behavior in Verbs. EMNLP 2016.

Pavlick et al. Adding Semantics to Data-Driven Paraphrasing. ACL 2015.

Pavlick et al. PPDB 2.0: Better paraphrase ranking, fine-grained entailment relations, word embeddings, and style classification. ACL 2015.

Pavlick et al. Domain-Specific Paraphrase Extraction. ACL 2015.

Rocktäschel et al. Reasoning about Entailment with Neural Attention. ICLR 2016.

Snow et al. Semantic taxonomy induction from heterogenous evidence. ACL 2006.

Thank you!