Learning Lexical Knowledge with Natural Tableau

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Natural Language Inference (NLI)

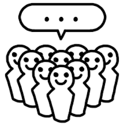
Recognizing Textual Entailment (RTE, Dagan et al., 2005):

Textual entailment is defined as a directional relationship between pairs of text expressions, denoted by T (the entailing “Text”) and H (the entailed “Hypothesis”).

We say that T entails H if humans reading T would typically infer that H is most likely true.

RTE aka Natural Language Inference (MacCartney & Manning, 2008)

Gold inference label =
Entailment|**C**ontradiction|**N**eutral



1	Both leading tenors are excellent.
2	Leading tenors who are excellent are indispensable.
E	Both leading tenors are indispensable.

Possibly multiple premises

Hypothesis/conclusion

Why natural logic machine learning?

Logic-based NLI systems are good at:

- Solve complex (but specific) problems
- Reasoning is interpretable

Neural models are at the top of the NLI leaderboards

But they are losing the NLI game:

- Difficult to scale up
- Incapable of learning from data

Natural logic can help here

Machine learning can help here

Learning lexical knowledge with Natural Tableau

Common to all knowledge-based systems is the difficulty of acquiring the background knowledge required to determine entailment (Dagan et al., 2013)

Semantic relations between words and short phrases:

puppy $\sqsubseteq$ dog

guitar | person

puppy $\sqsubseteq$ young dog

olive oil $\sqsubseteq$ cooking oil

tattered volleyball | broken volleyball

slice $\sqsubseteq$ cut

put on | take off

Learning lexical knowledge with Natural Tableau

Natural Tableau = Semantic tableau method for Natural Logic

$\neg(P \wedge Q) \vDash \neg P \vee \neg Q$

Propositional tableau rules

- $\wedge_{\mathbb{T}}$: $X \wedge Y : \mathbb{T}$ ⟹ $X : \mathbb{T}$, $Y : \mathbb{T}$
- $\wedge_{\mathbb{F}}$: $X \wedge Y : \mathbb{F}$ ⟹ $X : \mathbb{F}$ | $Y : \mathbb{F}$
- $\vee_{\mathbb{T}}$: $X \vee Y : \mathbb{T}$ ⟹ $X : \mathbb{T}$ | $Y : \mathbb{T}$
- $\vee_{\mathbb{F}}$: $X \vee Y : \mathbb{F}$ ⟹ $X : \mathbb{F}$, $Y : \mathbb{F}$
- $\neg_{\mathbb{F}}$: $\neg X : \mathbb{F}$ ⟹ $X : \mathbb{T}$
- $\neg_{\mathbb{T}}$: $\neg X : \mathbb{T}$ ⟹ $X : \mathbb{F}$
- $\times$: $X : \mathbb{T}$, $X : \mathbb{F}$ ⟹ $\times$

signed version

1 $\neg(P \wedge Q) : \mathbb{T}$

2 $\neg P \vee \neg Q : \mathbb{F}$

$\neg_{\mathbb{T}}[1]$

3 $P \wedge Q : \mathbb{F}$

$\vee_{\mathbb{F}}[2]$

4 $\neg P : \mathbb{F}$

5 $\neg Q : \mathbb{F}$

$\neg_{\mathbb{F}}[4]$

6 $P : \mathbb{T}$

$\neg_{\mathbb{F}}[5]$

7 $Q : \mathbb{T}$

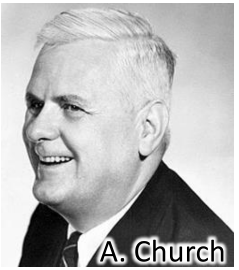
$\wedge_{\mathbb{F}}[3]$

8 $P : \mathbb{F}$ | 9 $Q : \mathbb{F}$

$\times[6,8]$ | $\times[7,9]$

10 $\times$ | 11 $\times$

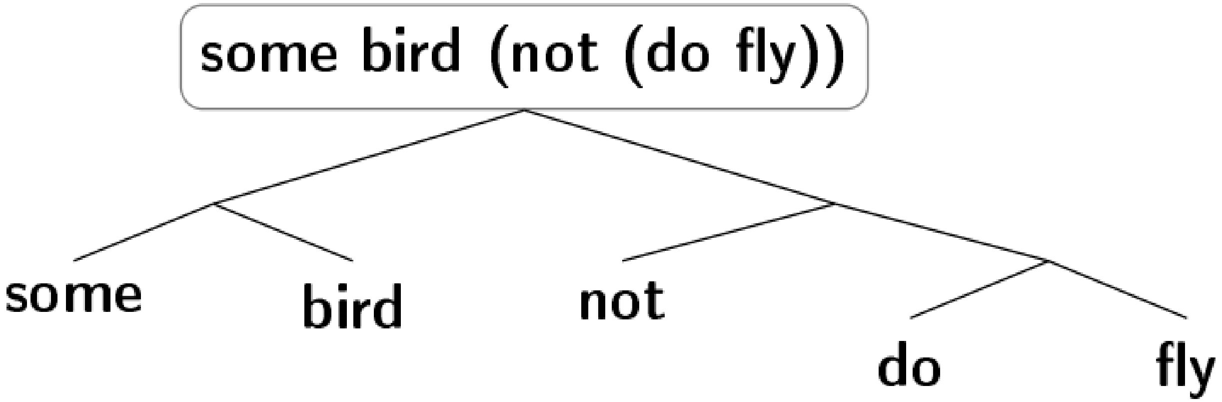
Simple type theory
(with simply typed λ-terms)



Natural Tableau: λ logical forms

No $\wedge$, $\vee$, $\rightarrow$, $\exists$, $\neg$, $\forall$ are used

Some bid doesn't fly



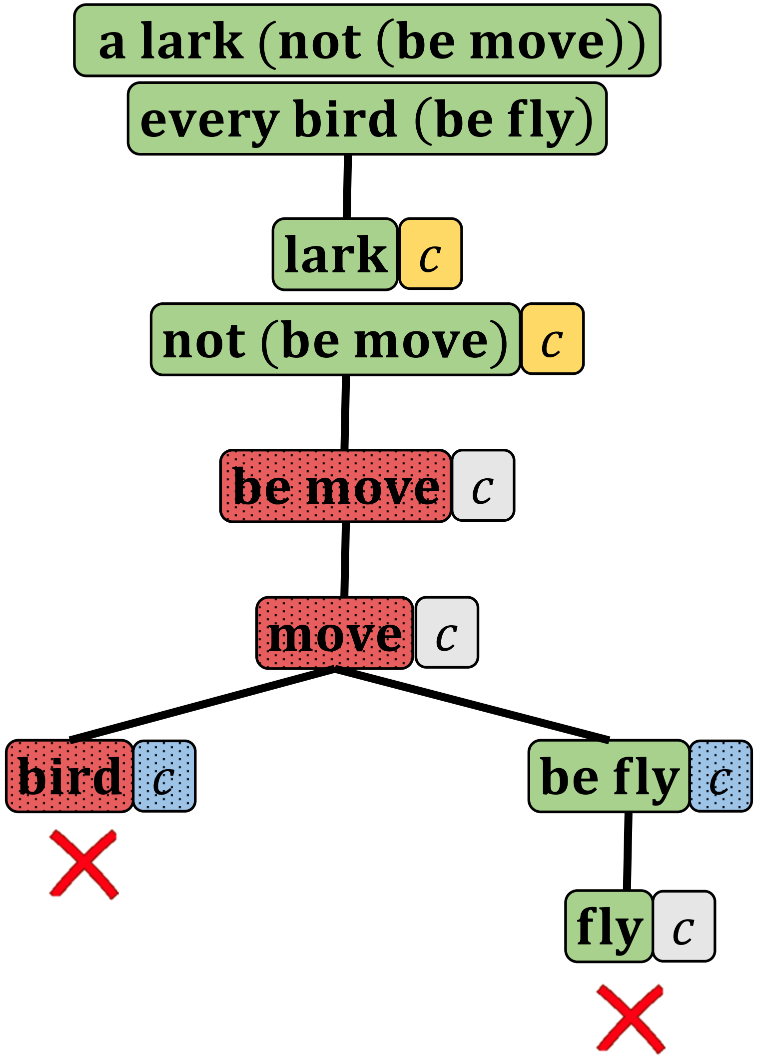
Every man loves some woman

$$\textbf{every man}\ (\lambda x.\ \textbf{some woman}\ (\lambda y.\ \textbf{love}\ y\ x))$$

$$\textbf{some woman}\ (\lambda y.\ \textbf{every man}\ (\textbf{love}\ y))$$

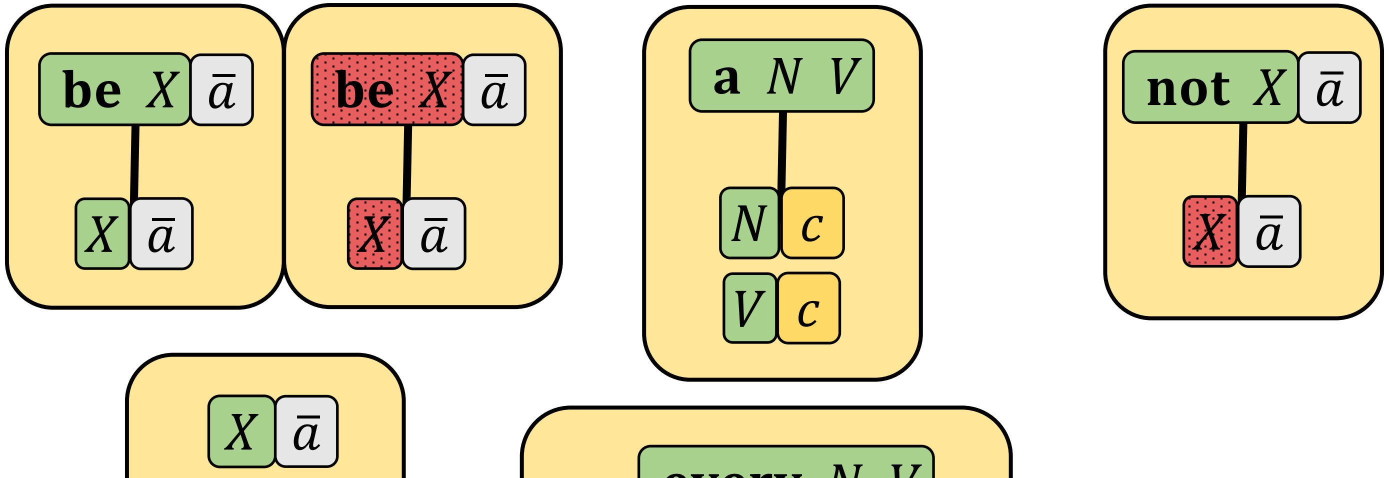
Muskens, R. (2010). An analytic tableau system for natural logic. LNCS, vol. 6042

Natural Tableau: analytic tableau system



Proved →

	A lark is not moving
C	Every bird is flying



Muskens, R. (2010). An analytic tableau system for natural logic. LNCS, vol. 6042


R. Muskens

Natural Tableau: wide-coverage version

More fine-grained node format: ~~$\lambda LF : \bar{a}$~~ $M : \lambda LF : \bar{a}$

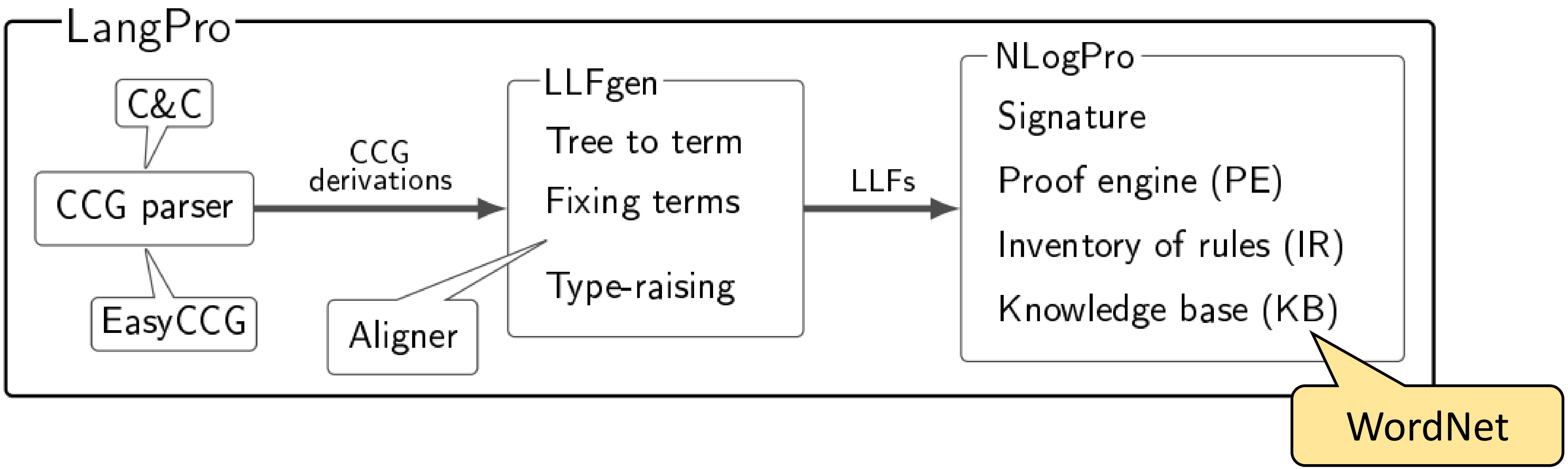
Incorporate syntactic types: $\{e, t\} + \{\boldsymbol{n},\ \boldsymbol{np},\ \boldsymbol{s},\ \boldsymbol{pp}\}$

More tableau rules for:

- Adjectives
- Prepositions/particles
- Passive constrictions
- Subcategorization
- Definite NPs
- Expletives
- Open compound nouns
- Light verb constructions
- Attitude verbs

Abzianidze, L. (2016). A natural proof system for natural language. Dissertation

Natural language theorem prover



ONLINE DEMO
https://naturallogic.pro/LangPro

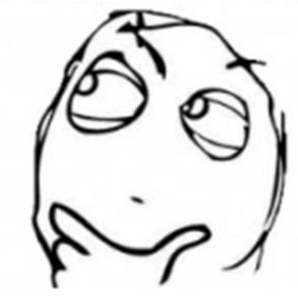
Abzianidze, L. (2017). LangPro: Natural language theorem prover. EMNLP
Abzianidze, L. (2016). Natural solution to FraCaS entailment problems. *SEM
Abzianidze, L. (2015). A tableau prover for natural logic and language. EMNLP

Problem of learning

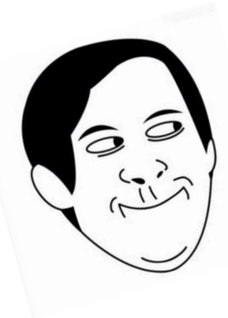
	Someone is holding a hedgehog
E	Someone is holding a small animal

ing datasets (Abzianidze, 2015; Mineshima et al., 2015). An important advantage of these systems (including ours) is that they are unsupervised, thus no training data is necessary and no parameters need to be adjusted.

Martınez-Gomez et al. (2017)



Despite many advantages, LangPro cannot learn from data



```
is_(european, person).
is_('boy', 'young man').
is_('young man', 'boy').
is_('polish', 'clean').
is_('jump', 'bounce').
is_('run', 'sprint').
is_('bikini', 'swimming suite').
is_(note, paper).
is_(fit, apply).
is_(wrestler, ringer).
is_(pour, put).
is_(vegetable, ingredient).
is_(fight, match).
is_(crowd, group).
```

Data-driven learning

Natural Tableau

Learning as abduction

	Someone is holding a hedgehog
E	Someone is holding a small animal

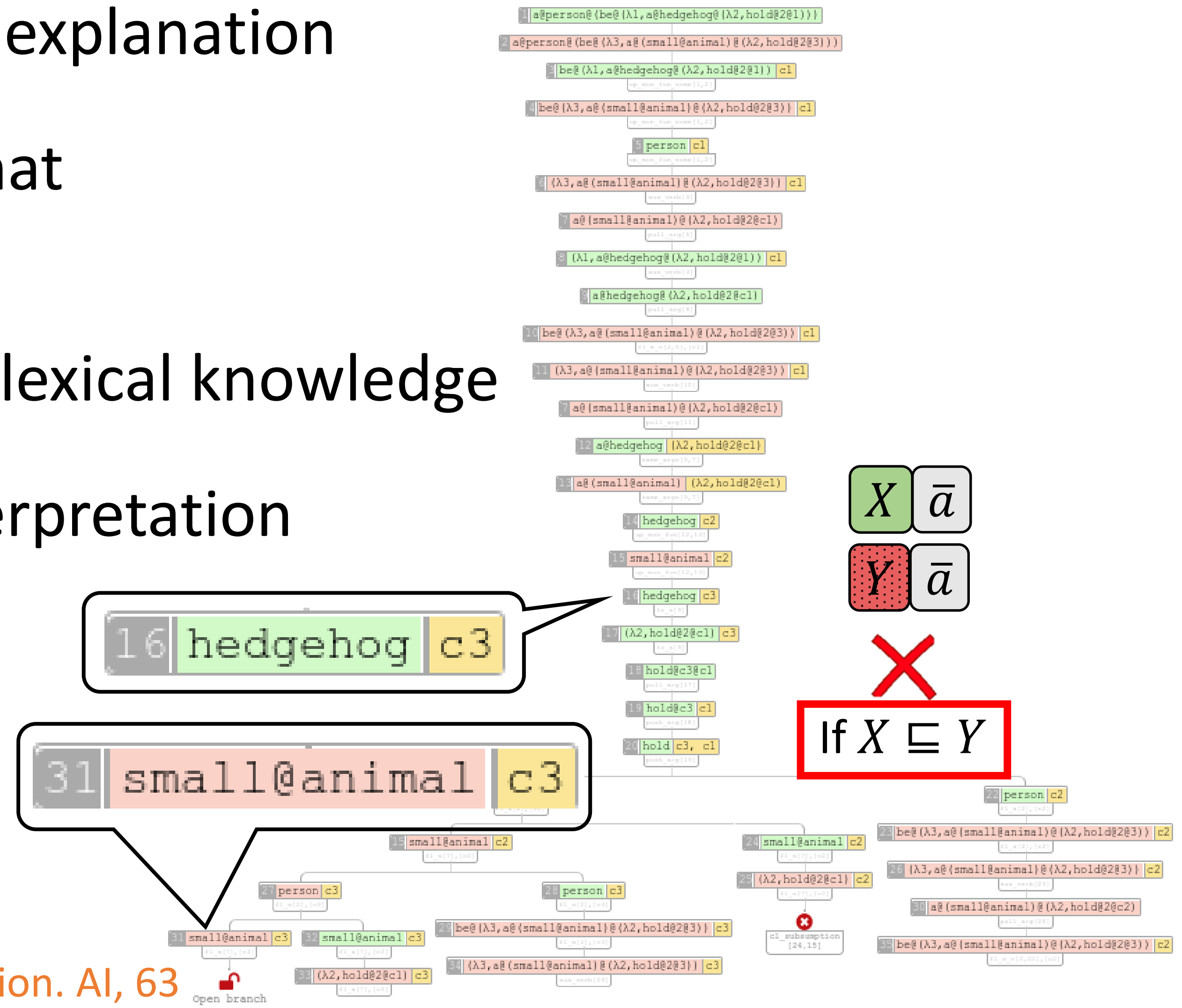
Abduction = inference to the best explanation

Infer the *best* lexical knowledge that closes a corresponding tableau

Best lexical knowledge = **minimal** lexical knowledge

Best interpretation = **minimal** interpretation

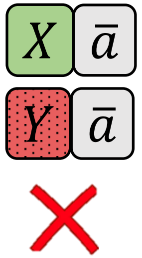
Hobbs et al. (1993)



Hobbs, Stickel, Appelt, Martin (1993). Interpretation as abduction. AI, 63

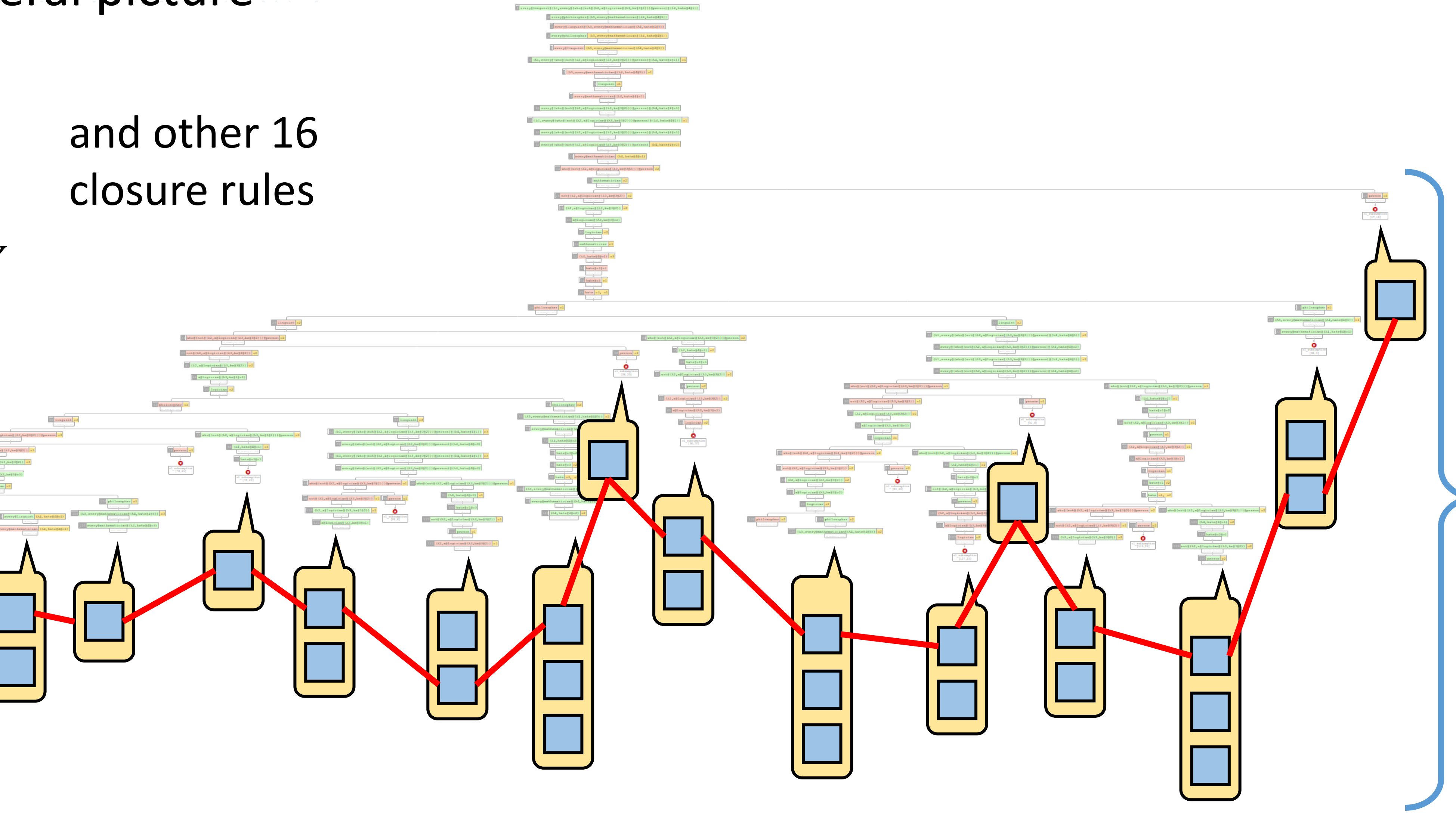
Inferring minimal closure knowledge

General picture



and other 16 closure rules

If $X \sqsubseteq Y$



Optimized inference

Selecting relations

Don't consider all nodes for closure search: X $\bar{a}$ $X\ Y$ $\bar{a}$ $X\ (Y\ Z)$ $\bar{a}$ $(X\ Y)\ Z$ $\bar{a}$

Filter inferred relations: $X\ r\ Y$

consistent with WordNet

with comparable POS tags

Selecting knowledge

! Only those knowledge that closes all open branches

table tennis $\sqsubseteq$ **ping pong**
tennis $\sqsubseteq$ **ping pong**
~~**table | tennis**~~

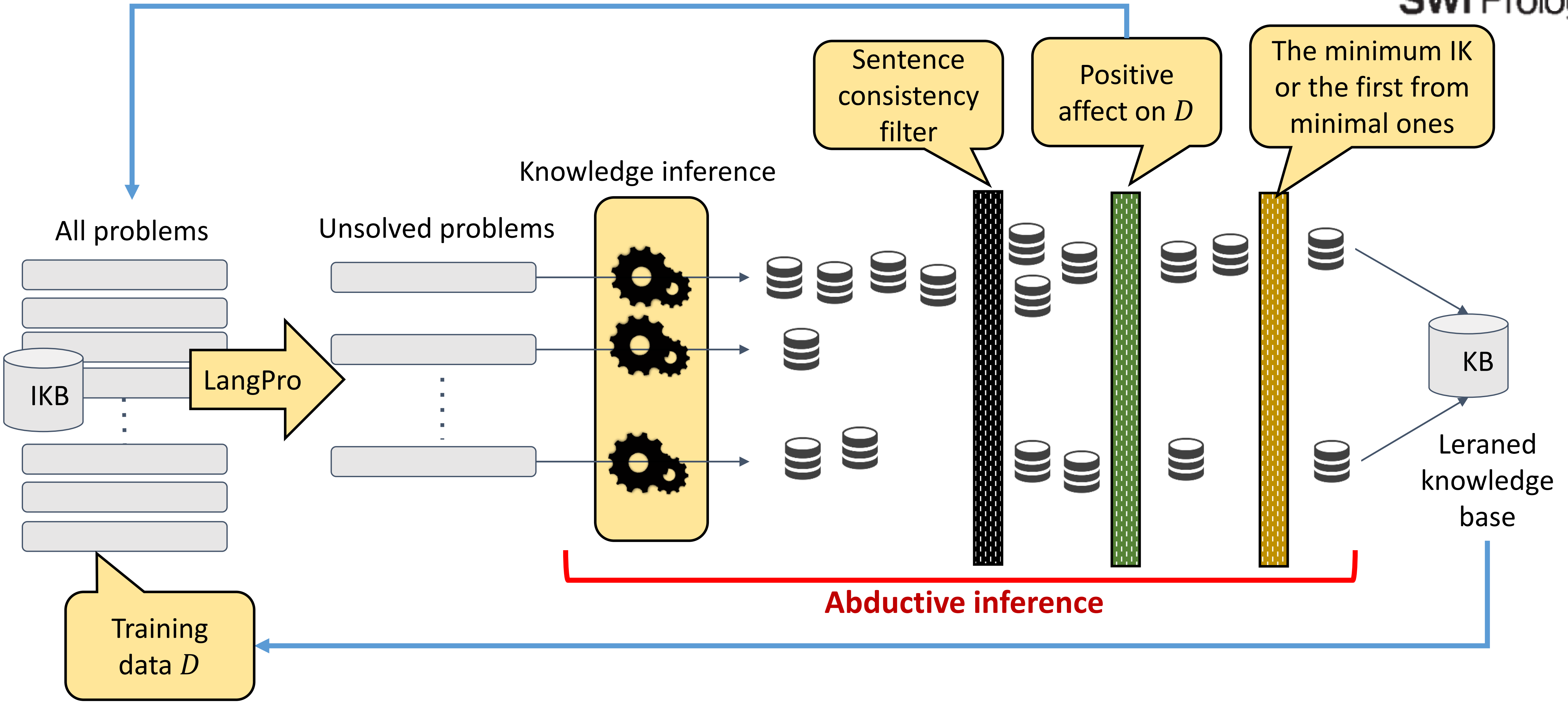
Inferred knowledge shouldn't make the sentences contradicting:

	Two men are playing table tennis
E	Two men are playing ping pong

Pick IKs with positive affect on the training data:

$|$ Solved problems **w IK** $| - |$ Solved problems **w/o IK** $| \geq 0$

Learning algorithm



Results

Experiments

Sentences Involving Compositional Knowledge (SICK, Marelli et al., 2014)

E (29%), **C** (15%), **N** (56%)

Train	4,500	stratified 3-fold cross validation
Dev	500	developing the abductive learning component
Test	4927	held-out data

3-fold CV:

Concurrent run on 24 CPUs

Max 100 rule application – 24min

Max 50 rule application – 16min

Peregrine HPC cluster

2 loops is sufficient for 3,000 training samples: 169 IKs, 8 IKs

university of groningen

Results

3-fold CV on SICK-train (using the C&C parser)

Rule applications	Hand-crafted KB	WordNet	Av. Accuracy on train part	Av. accuracy on test part	Av. Precision on test part
50	✓	✓	86.7	82.0	94.7
50	✗	✓	86.6	81.7	94.8
50	✗	✗	85.6	78.8	93.9
100	✗	✓	86.9	81.8	-
100	✗	✗	85.8	78.9	-

Comparison to previous versions

Train on SICK-train and evaluate on SICK-test (using the C&C parser)

LangPro + C&C parser	Rule applications	Hand-crafted KB	Accuracy on train part	Accuracy on test part	Precision on test part
Abduction	100	✔	87.3	82.4	95.1
-	100	✗	87.2	82.4	95.3
(2015)	50	✔	-	79.5	98.0
-	800	✔	-	79.9	98.0
(2016)	800	✔	-	81.1	97.5

BERT (base, uncased) : **86.74**
(Devlin et al. 2019)

Logic-based systems SOTA: **83.68**
Martınez-Gomez et al. (2017)

Learned *knowledge*

jump | stand

motorbike | motorcyclist

person | vehicle

run | walk

acrobatics $\sqsubseteq$ trick

baby panda $\sqsubseteq$ cub

elderly woman $\sqsubseteq$ old person

guy $\sqsubseteq$ bloke

brown | large

dog | white animal

boil $\sqsubseteq$ stir

camera $\sqsubseteq$ photo

container $\sqsubseteq$ box

device $\sqsubseteq$ telephone

man $\sqsubseteq$ model

woman $\sqsubseteq$ girl

	Three friends are making faces for the camera
E	Three friends are making faces for a photo

Missed knowledge

	Someone is **peeling** a banana
E	Someone is **removing the peel** of a banana

	People are walking outside the building that **has several murals** on it
E	Several people are in front of a **colorful** building

	People **wearing costumes** are gathering in a forest and are looking in the same direction
E	**Masked** people are looking in the same direction in a forest

	A person is **riding** a motorcycle
C	A person is **standing near** a motorcycle

Related work

Martınez-Gomez et al. (2017)

Abduction is not as learning but retrieving from WordNet

Yoshikawa et al. (2018)

A trainable component scoring lexical relations

Beltagy et al. (2017)

Probabilistic FOL with Markov Logic Networks

Employs SVM to map probabilities to classes

Uses automatically extracted, classified and weighted rules

Yoshikawa et al. (2018). Combining Axiom Injection and Knowledge Base Completion for Efficient Natural Language Inference. AAAI

Martınez-Gomez et al. (2017). On-demand Injection of Lexical Knowledge for Recognising Textual Entailment. EACL

Beltagy et al. (2017). Representing Meaning with a Combination of Logical and Distributional Models. CL

Conclusion & next steps

Is it possible that a theorem prover learns from data:

Learning as abduction works!

Why are we doing this?

Logic-based systems are explanatory and reliable

Push logic-based systems to their limits

They can be used to evaluate NLI datasets

What's next?

Finalize experiments, less restricted search (ongoing research)

Can we learn inference rules?

Try other NLI datasets

Thank you

ONLINE DEMO https://naturallogic.pro/LangPro

GitHub https://github.com/kovvalsky/LangPro

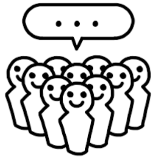
@FiboKowalsky

https://i.pinimg.com/originals/47/bb/69/47bb69967dbd89eef556681e4f318db2.gif

https://mir-s3-cdn-cf.behance.net/project_modules/disp/46f6c836224077.57dedf2450286.gif

https://giphy.com/gifs/research-madebydot-gifathon-26FPC5oAdfeFPkQQE

https://upload.wikimedia.org/wikipedia/commons/thumb/3/38/201705_Scientist_desk_F.svg/480px-201705_Scientist_desk_F.svg.png



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https://pngimg.com/uploads/sparrow/sparrow_PNG26.png

https://freesvg.org/img/hand-pencil.png