Explaining (how to improve) Diagnostic Reasoning

— *The FAMULUS Project* —

Please don't hesitate to ask questions during the talk!

Claudia Schulz

15/01/2020 XAI Seminar

FAMULUS

http://famulus-project.de

LMU LUDWIG-MAXIMILIANS-UNIVERSITÄT MÜNCHEN
LMU KLINIKUM DER UNIVERSITÄT MÜNCHEN
DAM
UBIQUITOUS KNOWLEDGE PROCESSING
TECHNISCHE UNIVERSITÄT DARMSTADT

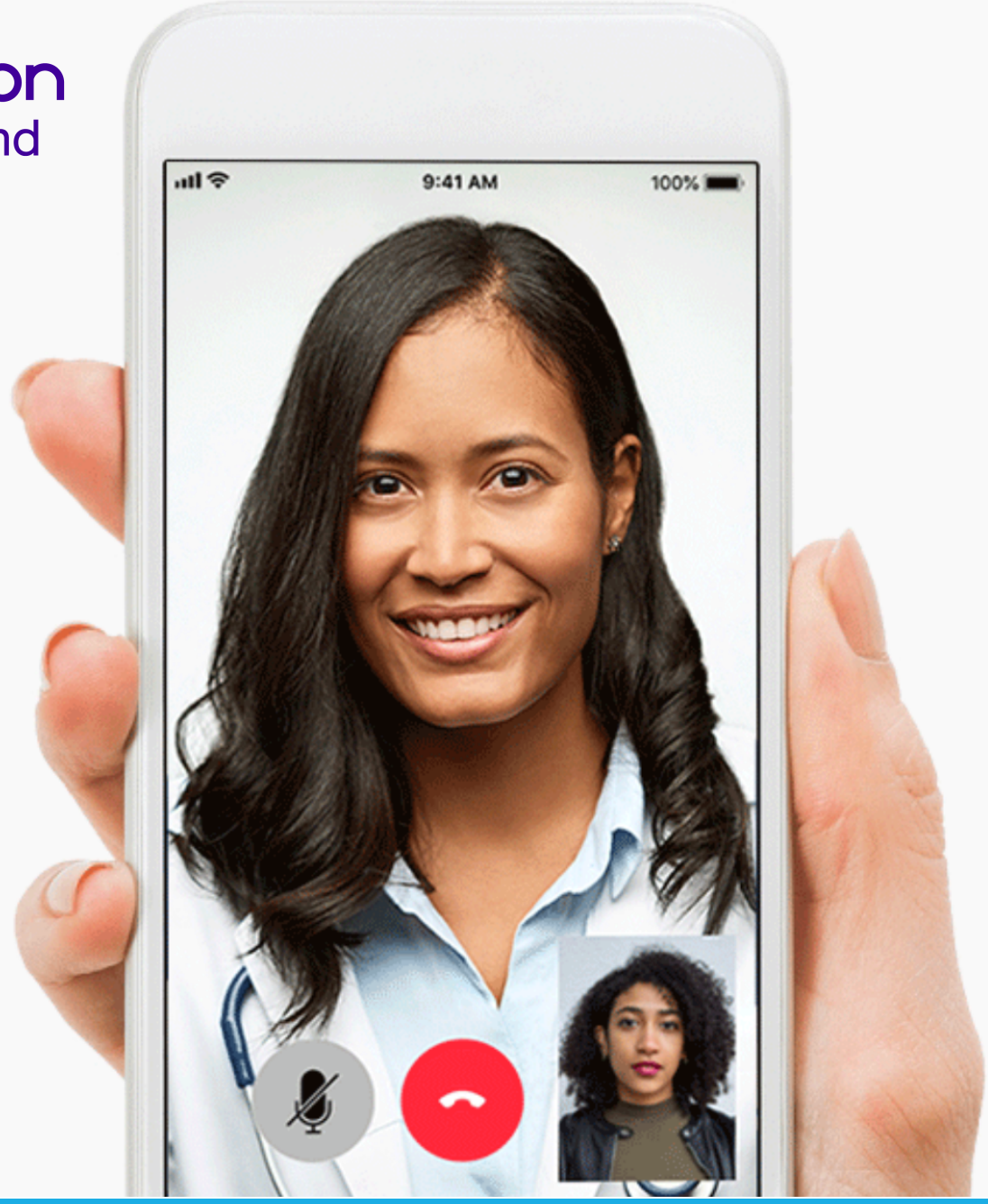
NHS GP appointments just a tap away*

babylon
GP at hand

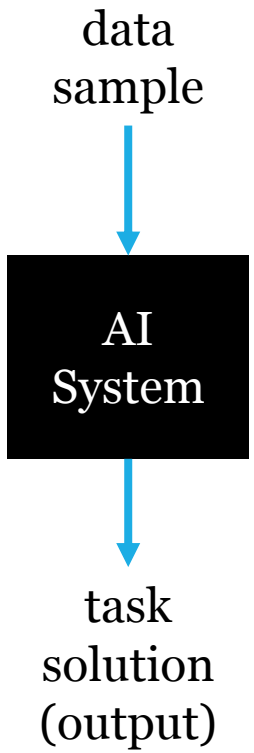
- **On mobile** in minutes 24/7
- **In person** at a choice of locations
- **Free** digital Healthcheck

Get Started

*To register you will need to switch from your current GP practice. Once an application is made, a registration period will apply before you are able to access the service. Available for people living or working within the catchment area of one of our clinic locations.



Explainable AI



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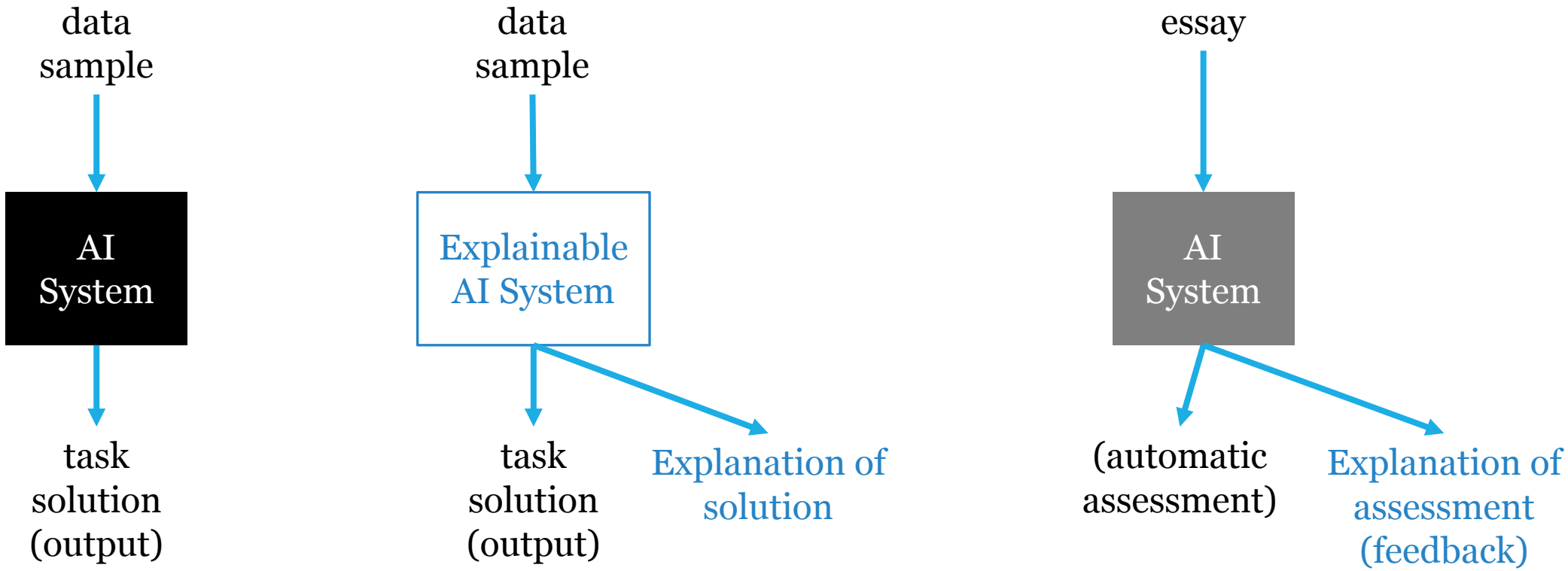
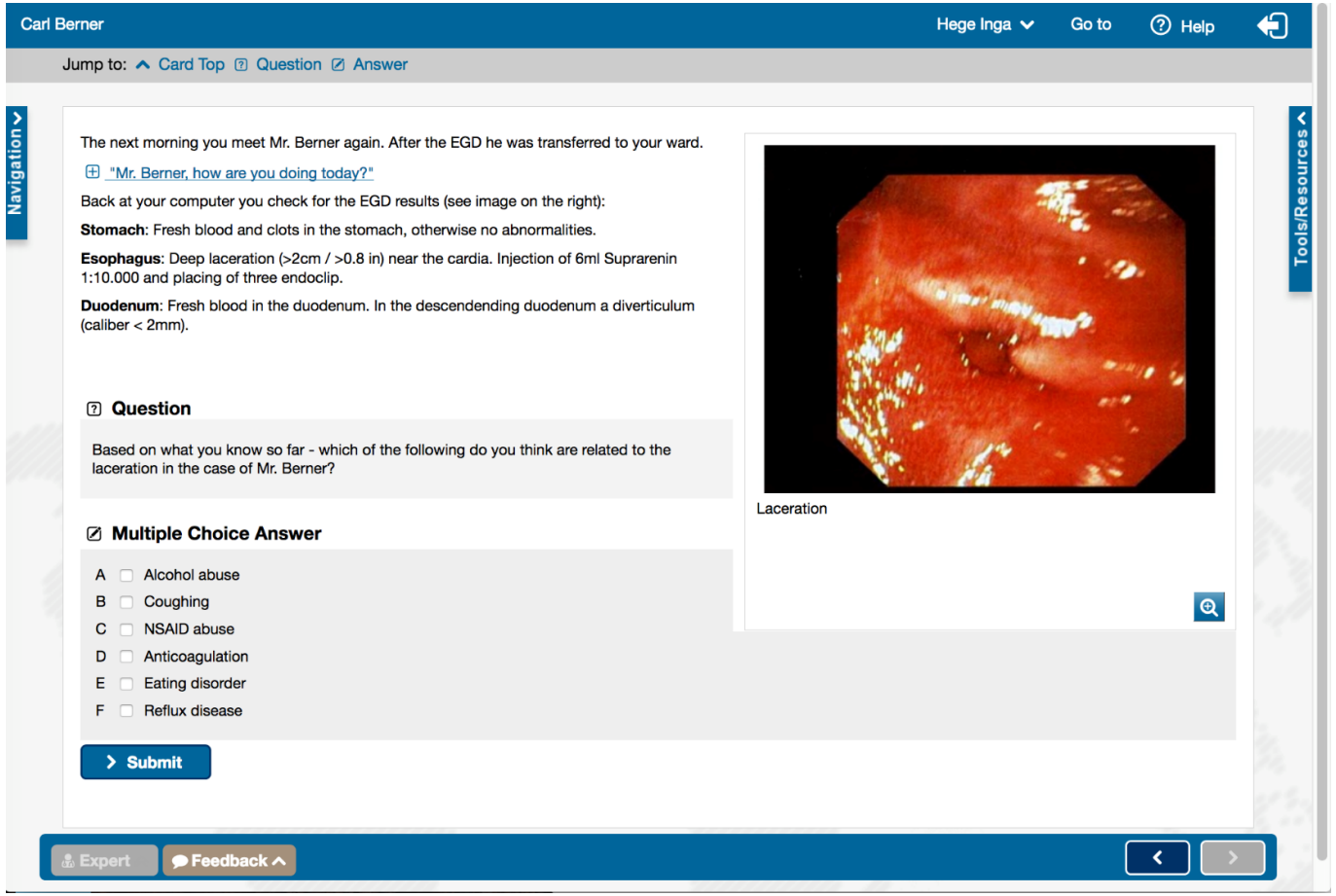


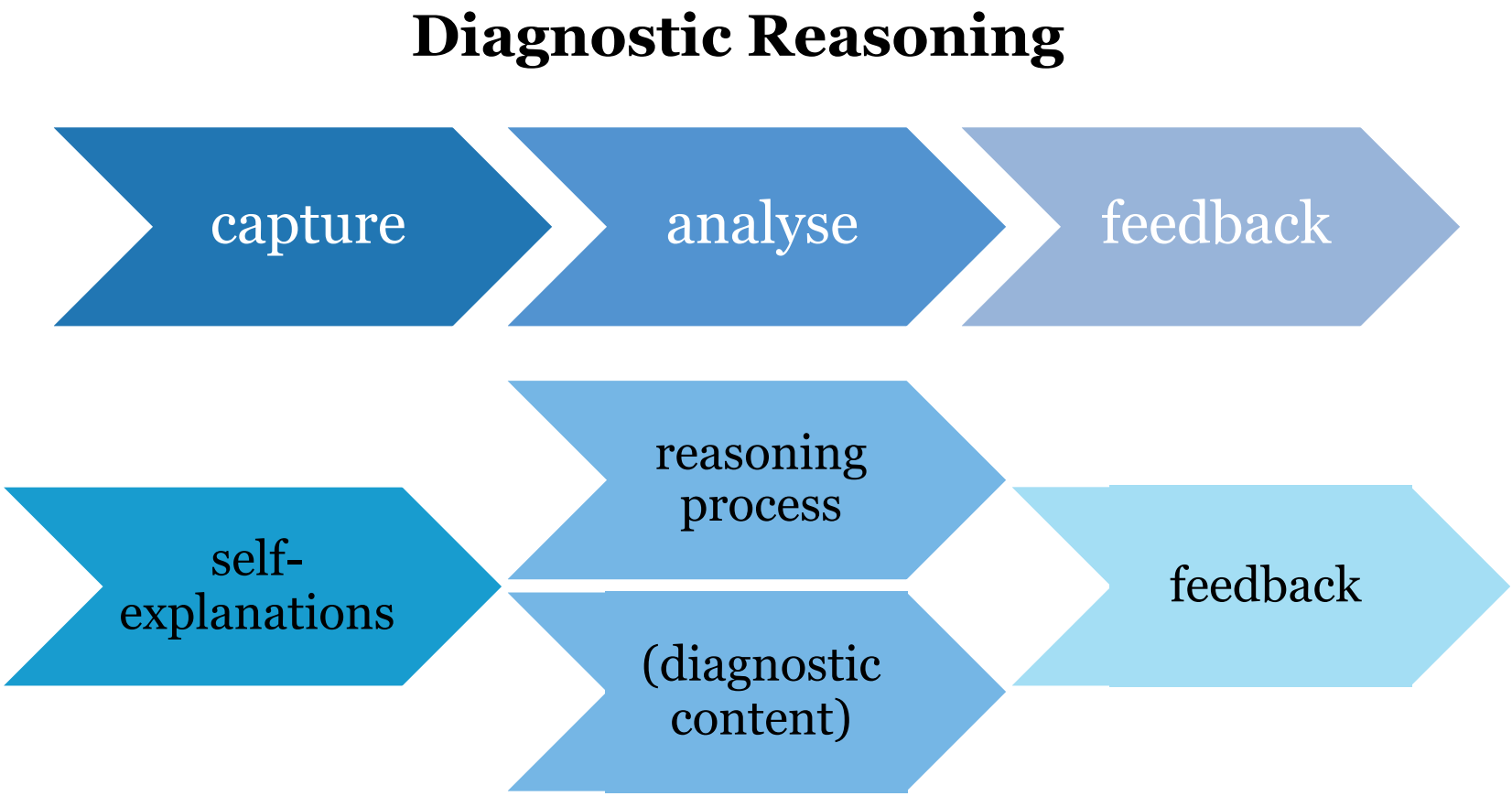
Learning Diagnostic Reasoning

Diagnostic Reasoning

Case Simulation



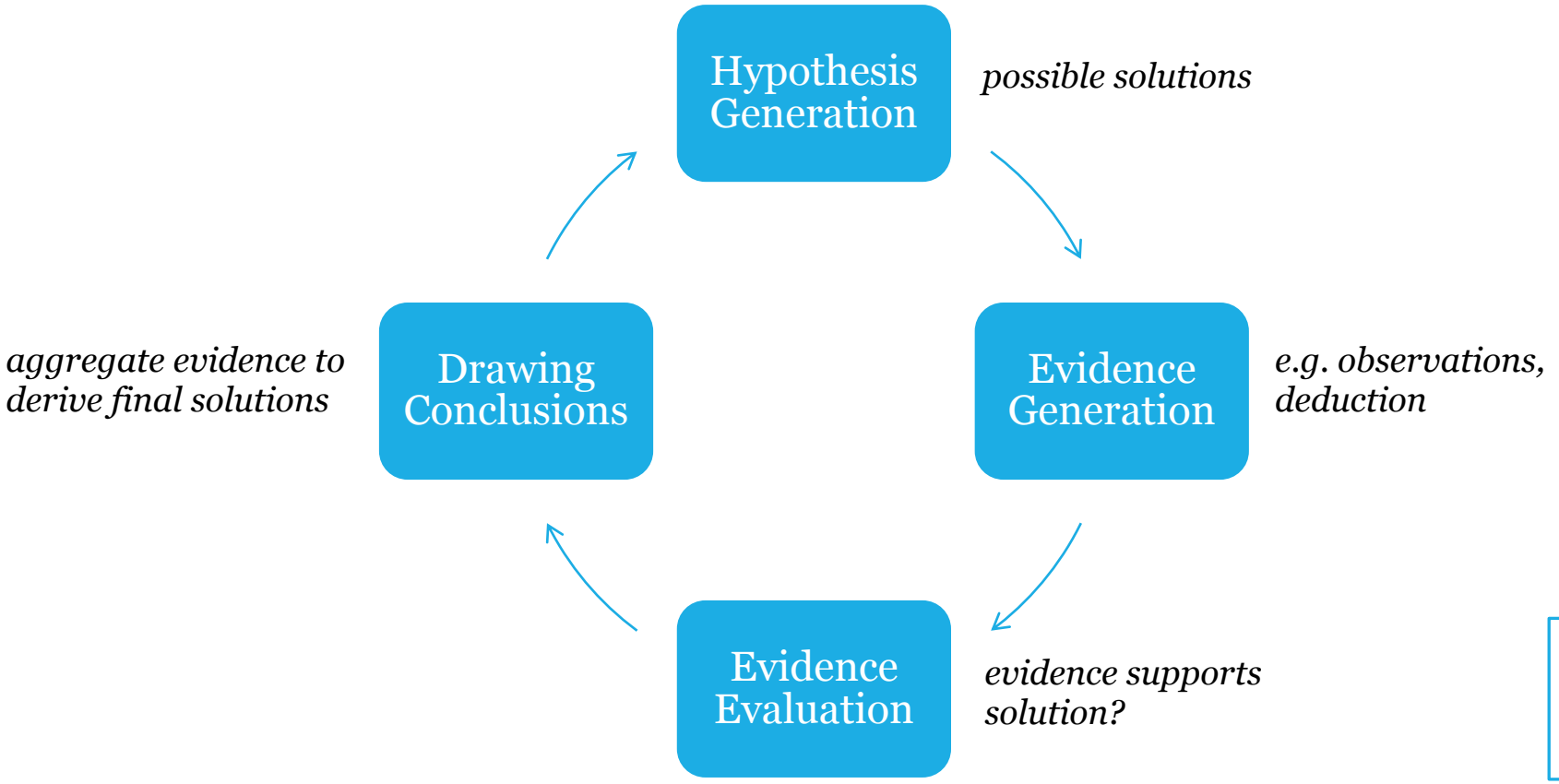
Individual Feedback



Capture: Self-Explanation

The patient reports to be lethargic and feverish.
From the anamnesis I learned that he had purulent tonsilitis and is still suffering from symptoms.
I first performed some laboratory tests and notice the decreased number of lymphocytes, which can be indicative of a bone marrow disease or an HIV infection.
The HIV test is positive.
However, the results from the blood cultures are negative, so it is a virus, parasite, or a fungal infection causing the symptoms.

Analyse: Reasoning Process



Diagnostic reasoning steps (epistemic activities)
Fischer et al. 2014

Self-Explanation with Feedback

Feedback

Well done for thinking about different possible solutions, the generation of **hypotheses** is an important part of diagnosis.

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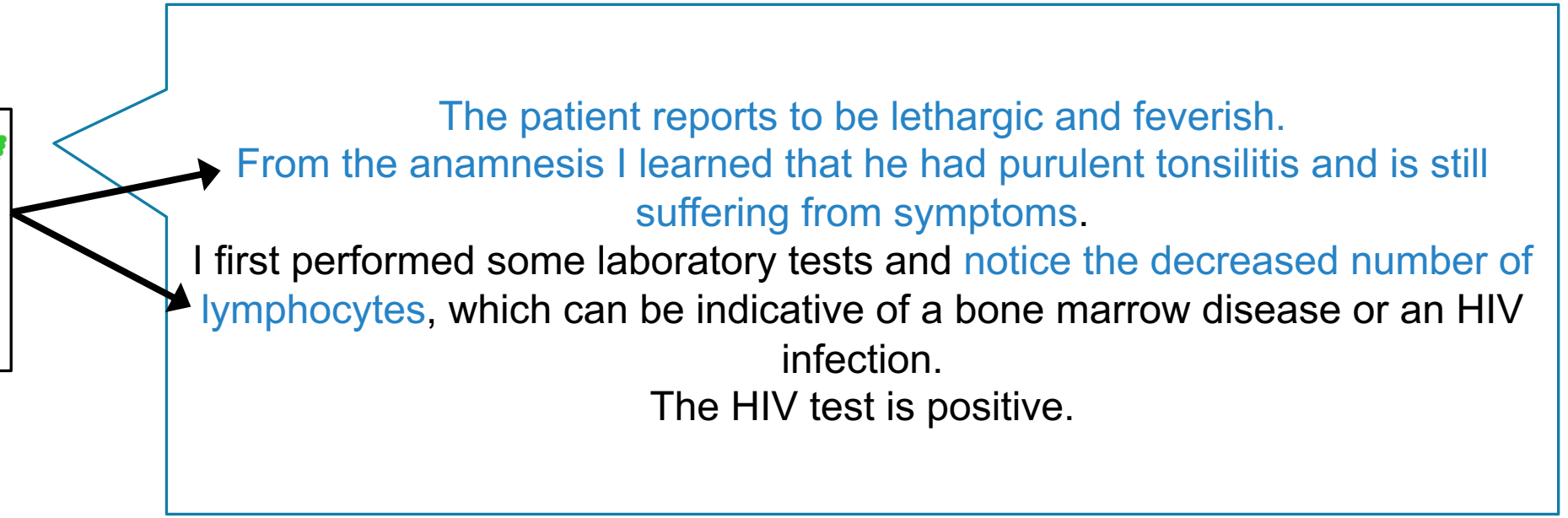
Self-Explanation with Feedback

Feedback

Good that you considered the different **observations** and test results.



Self-Explanation with Feedback

Feedback

After collecting and considering all evidence, you should decide on the most likely **diagnosis**. This is an important duty of a doctor.

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Self-Explanation with Reasoning Steps

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Hypothesis Generation
Evidence Generation
Evidence Evaluation
Drawing Conclusions

Detecting Diagnostic Reasoning Steps

1) **Corpus Creation**
2) **Automatic Detection**

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Corpus Creation

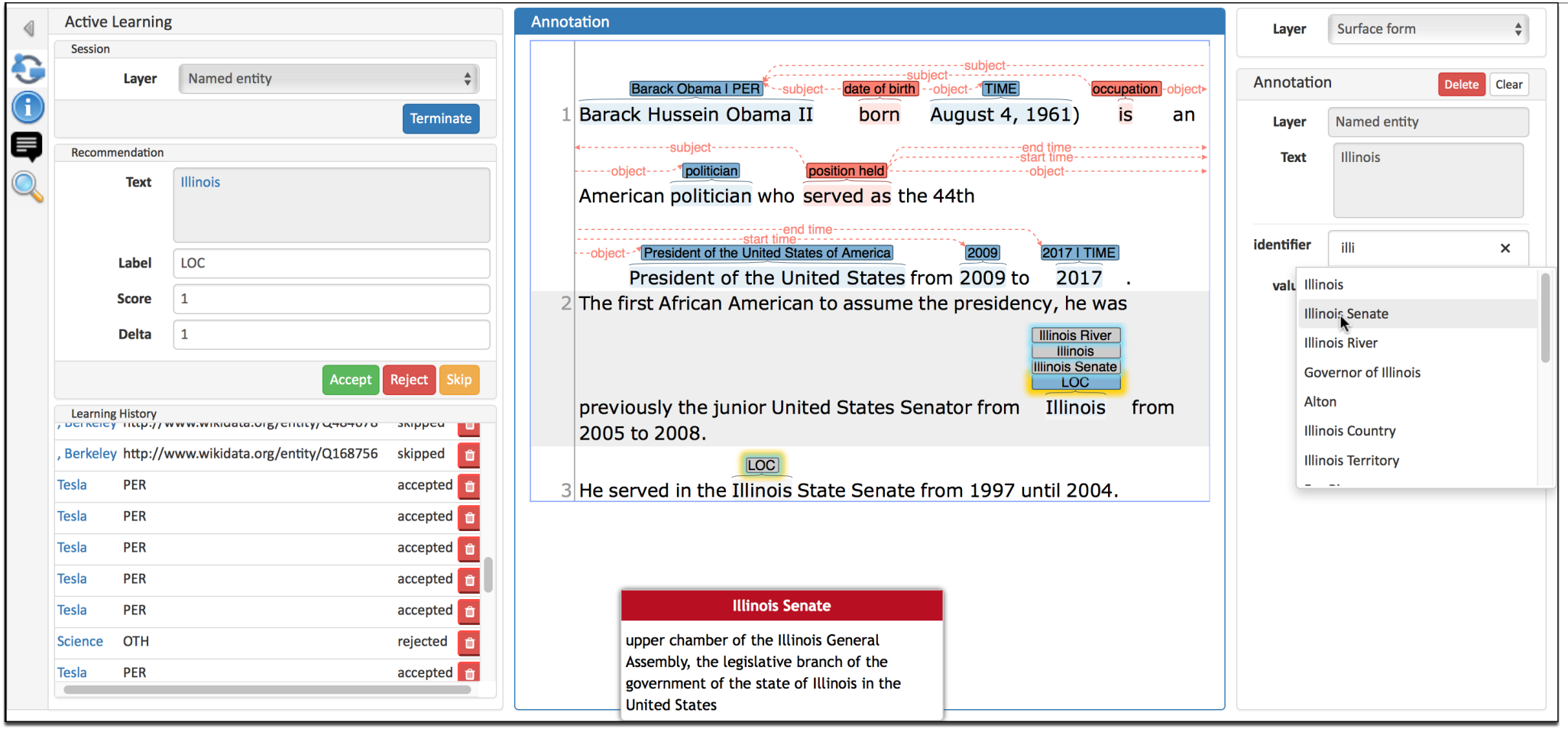
Schulz, Meyer, Gurevych. "Challenges in the Automatic Analysis of Students' Diagnostic Reasoning."
Proceedings of the 33rd AAAI Conference on Artificial Intelligence. 2019.

Corpus Creation

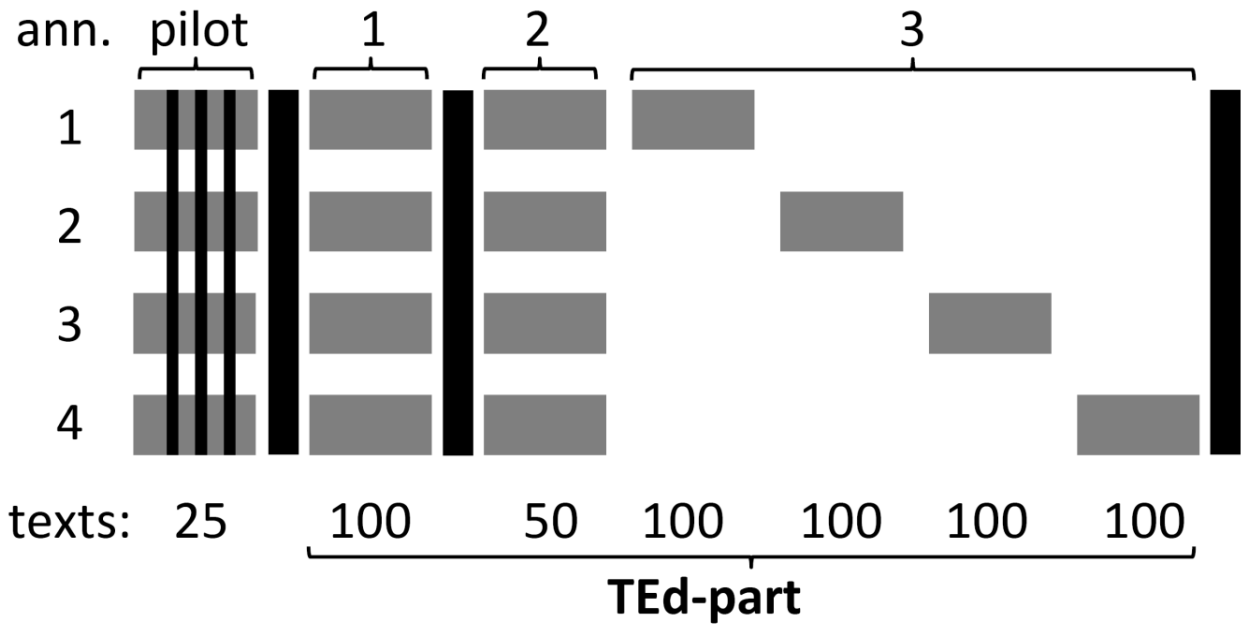
- Two domains:
  - Medicine Domain (MeD): 1131 self-explanations → 650 used
  - Teaching Domain (TeD): 976 self-explanations → 550 used
- (Domain) Expert annotators
- Cross-domain annotation scheme
  - Segmentation + classification
  - Easily adaptable to new domains
- German

INCEpTION

https://inception-project.github.io/



Corpus Creation



Inter-Annotator Agreement

Domain	α_U	α_U-HG	α_U-EG	α_U-EE	α_U-DC	α_U-segment	$\uparrow\alpha_U$-pair	$\downarrow\alpha_U$-pair
medicine	0.67	0.60	0.65	0.75	0.56	0.86	0.71	0.62
teaching	0.65	0.43	0.56	0.75	0.49	0.82	0.67	0.63

Table 1: Inter annotator agreement (IAA) in terms of Krippendorff's α_U.

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Domain	α_U-HG&DC	α_U-EE&DC	α_U-HG&EE	α_U-EG&EE	α_U-EG&HG	α_U-EG&DC
medicine	**0.71**	**0.85**	**0.78**	**0.78**	0.61	0.56
teaching	**0.62**	**0.81**	**0.77**	0.72	0.47	0.48

Table 2: IAA (α_U) when merging epistemic activities. Bold indicates a value higher than both single activities.

Corpus Statistics

- majority vote (4/5, 3/4) + annotator meeting
- MeD av. length: 63.8 tokens
- TeD av. Length: 100.2 tokens

		EG	EE	HG	DC
MeD	#	219	2124	623	493
	av. #	0.35	3.27	0.96	0.76
	av len.	10.1	11.6	9.0	16.0
TeD	#	354	2671	311	444
	av. #	0.64	4.86	0.57	0.81
	av. len.	12.4	12.1	13.5	15.4

Table 3: Corpus statistics in terms of absolute number (#), average number per text (av. #), and average number of tokens (av. len), where EE/EG (and similar) denotes an overlap of an EG and EE segment.

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Corpus Statistics

- majority vote (4/5, 3/4) + annotator meeting
- MeD av. length: 63.8 tokens
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The x-ray and the subsequent MRI confirmed a vertebral body fracture

		EG	EE	HG	DC	EG/EE	HG/DC	DC/EE	EG/HG	HG/EE	EG/DC
MeD	#	219	2124	623	493	5	4	342	0	12	4
	av. #	0.35	3.27	0.96	0.76	–	–	–	–	–	–
	av len.	10.1	11.6	9.0	16.0	3.8	8.5	9.8	–	5.7	6.8
TeD	#	354	2671	311	444	8	2	143	3	8	3
	av. #	0.64	4.86	0.57	0.81	–	–	–	–	–	–
	av. len.	12.4	12.1	13.5	15.4	7.9	22.0	10.9	6.0	11.1	11.7

Table 3: Corpus statistics in terms of absolute number (#), average number per text (av. #), and average number of tokens (av. len), where EE/EG (and similar) denotes an overlap of an EG and EE segment.

Detecting Diagnostic Reasoning Steps

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2) **Automatic Detection**

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Hypothesis Generation
Evidence Generation
Evidence Evaluation
Drawing Conclusions

Automatic Detection of Diagnostic Reasoning Steps

Schulz, Meyer, Gurevych. "Challenges in the Automatic Analysis of Students' Diagnostic Reasoning." *Proceedings of the 33rd AAAI Conference on Artificial Intelligence*. 2019.

Automatic Detection

3 Challenges:

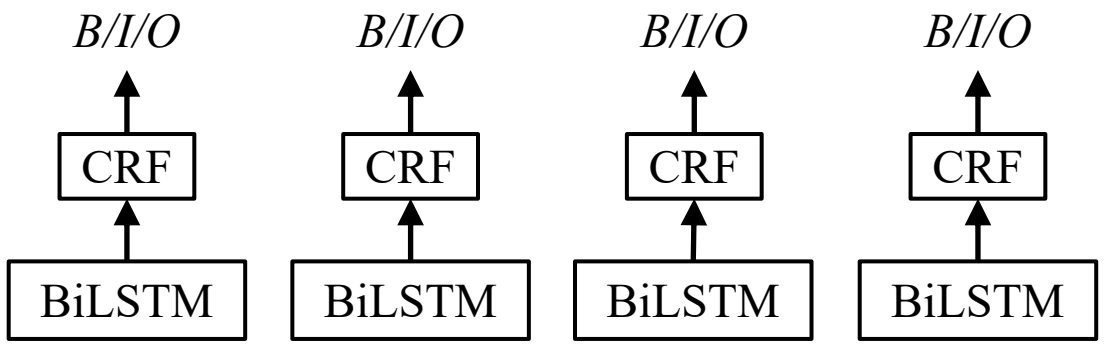
1. segments of arbitrary length (C1),
2. distinguishing different epistemic activity types (C2)
3. overlapping epistemic activity segments (C3)

Multi-class sequence labelling
$C = (\{B, I\} \times A) \cup \{O\}$
$A = \{HG, EG, EE, DC\}$

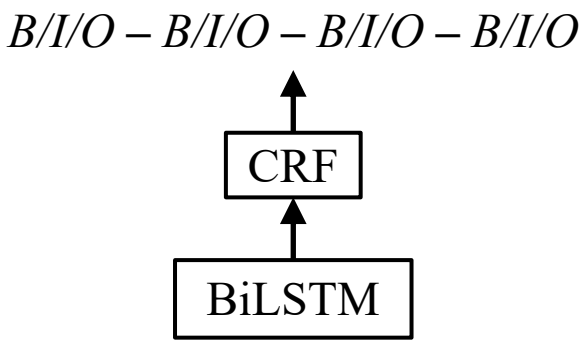
→ **multi-label problem:** $C' \subset C$

Approach: 3 problem transformations

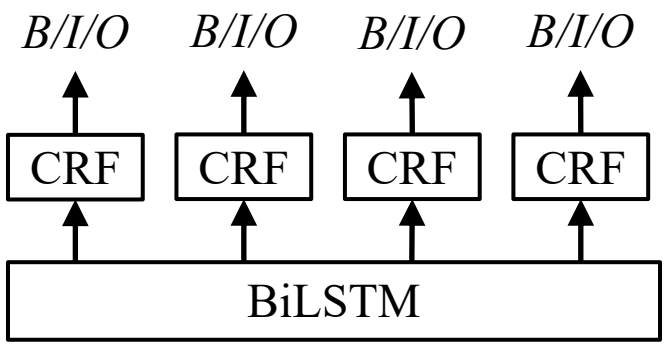
Problem Transformations



SEPARATE:
multiple (single-label)
multi-class problems



CONCAT:
unique (single-label)
multi-class problem

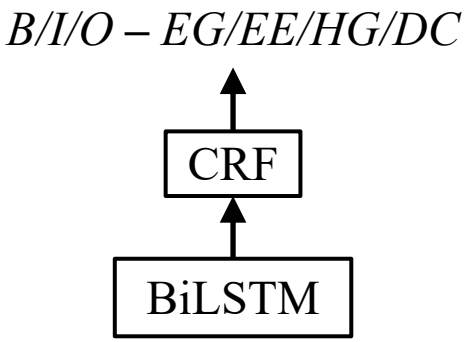


MULTI-OUTPUT:
Multidimensional
classification problem

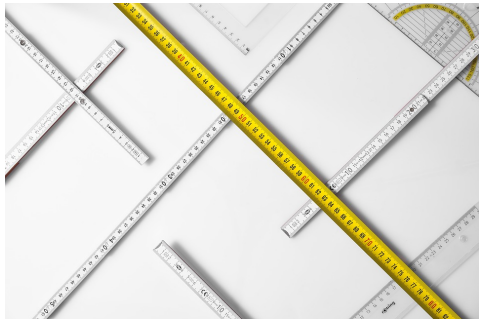
Baseline Transformations

1. PREF-BASELINE: unique (single-label) multi-class problem
   - Without overlaps
   - Using preference order: DC > HG > EG > EE

2. MAJ-BASELNE: I-EE for all tokens



Evaluation Metrics



- Hamming Loss

$$HL = \frac{1}{|\mathcal{X}|}\sum_{x\in\mathcal{X}}\frac{1}{|C|}\sum_{c\in C}\mathbf{xor}(y_{x,c},\ \hat{y}_{x,c})$$

$$y_{x,c} = \begin{cases} 1 & if\ token\ x\ has\ label\ c \\ 0 & otherwise \end{cases}$$

- C1 (Segmentation)

$$M_S(a) = macro\text{-}F1(C_a, \mathcal{X})$$

$$for\ a\ \in A = \{HG, EG, EE, DC\}$$

$$C_{HG} = \{B-HG, I-HG, O-HG\}$$

- C2 (Type Distinction)

$$M_A = macro\text{-}F1(\mathscr{P}(A), \mathcal{X})$$

- C3 (Overlaps)

$$M_O(a) = macro\text{-}F1(C_a, \mathcal{X}_{\text{overlap}})$$

Automatic Detection: Results

$$HL = \frac{1}{|\mathcal{X}|} \sum_{x \in \mathcal{X}} \frac{1}{|C|} \sum_{c \in C} \mathbf{xor}(y_{x,c},\ \hat{y}_{x,c})$$

		HL	M_S				M_A	M_O			
	Architecture	all	EG	EE	HG	DC	all	EG	EE	HG	DC
MeD	MULTI-OUTPUT	0.07	71.60	80.20^{+}	69.28	65.32	22.21^{+}	63.09	66.39^{+}	45.50	44.76
	SEPARATE	0.07	70.87	80.24^{+}	68.53	65.80	21.25^{+}	63.15	65.31^{+}	50.26	49.26
	CONCAT	0.06^{+++}	71.05	79.96^{+}	69.36	65.18	23.01^{++}	67.86	66.43^{+}	44.51	45.40
	PREF-BASELINE	0.07	70.02	75.46	69.32	65.74	19.77	52.91	38.87	46.34	49.03
	MAJ-BA									1	1.39
	human up									8	76.50
TeD	MULTI-O									1+	47.10
	SEPARATE	0.07	76.38	79.47^{+}	57.05	57.52	18.34	54.68	78.89^{+++}	32.09	36.11
	CONCAT	0.06^{++}	78.71^{+}	79.07^{+}	57.12	62.53^{+}	21.68^{+++}	56.75	68.75^{+}	32.51	51.97^{+}
	PREF-BASELINE	0.06	77.60	77.21	55.67	61.02	18.93	57.25	45.15	36.62	49.71
	MAJ-BASELINE	0.11	31.75	23.11	32.03	30.97	4.42	31.21	30.75	32.61	6.28
	human upper bound	0.03	93.29	90.71	81.77	82.11	30.58	78.68	88.99	79.96	95.04

Conclusion: No distinction possible between neural architectures!

Automatic Detection: Results

$$M_S(a) = \textit{macro-F1}(C_a, \mathcal{X})$$

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	MAJ-BASELINE	0.11	32.70	23.49	30.48	29.96	4.25	33.13	31.00	32.61	1.39
	human upper bound	0.04	85.61	90.25	86.37	85.58	35.06	100.00	76.15	91.38	76.50
TeD	MULTI-OUTPUT	0.07	78.53	78.87^{+}	57.16	61.77	19.96^{+}	58.42	71.98^{+}	32.61^{+}	47.10
	SEPARATE	0.07	76.38	79.47^{+}	57.05	57.52	18.34	54.68	78.89^{+++}	32.09	36.11
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Automatic Detection: Results

$$M_S(a) = \textit{macro-F1}(C_a, \mathcal{X})$$

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Automatic Detection: Results

$$M_S(a) = \textit{macro-F1}(C_a, \mathcal{X})$$

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Conclusion: Neural architectures perform segmentation reasonably well!

Automatic Detection: Results

Upper Bound: 62.5

$$M_A = \textit{macro-F1}(\mathscr{P}(A), \mathcal{X})$$

		HL	M_S				M_A	M_O			
	Architecture	all	EG	EE	HG	DC	all	EG	EE	HG	DC
MeD	MULTI-OUTPUT	0.07	71.60	80.20^{+}	69.28	65.32	22.21^{+}	63.09	66.39^{+}	45.50	44.76
	SEPARATE	0.07	70.87	80.24^{+}	68.53	65.80	21.25^{+}	63.15	65.31^{+}	50.26	49.26
	CONCAT	0.06^{+++}	71.05	79.96^{+}	69.36	65.18	23.01^{++}	67.86	66.43^{+}	44.51	45.40
	PREF-BASELINE	0.07	70.02	75.46	69.32	65.74	19.77	52.91	38.87	46.34	49.03
	MAJ-BA										1.39
	human up										76.50
TeD	MULTI-O										47.10
	SEPARATE	0.07	76.38	79.47^{+}	57.05	57.52	18.34	54.68	78.89^{+++}	32.09	36.11
	CONCAT	0.06^{++}	78.71^{+}	79.07^{+}	57.12	62.53^{+}	21.68^{+++}	56.75	68.75^{+}	32.51	51.97^{+}
	PREF-BASELINE	0.06	77.60	77.21	55.67	61.02	18.93	57.25	45.15	36.62	49.71
	MAJ-BASELINE	0.11	31.75	23.11	32.03	30.97	4.42	31.21	30.75	32.61	6.28
	human upper bound	0.03	93.29	90.71	81.77	82.11	30.58	78.68	88.99	79.96	95.04

Conclusion: Distinction of different reasoning steps is highly challenging!

Automatic Detection: Results

Upper Bound: 62.5

$M_A = \textit{macro-F1}(\mathscr{P}(A), \mathcal{X})$

		HL	M_S				M_A	M_O			
	Architecture	all	EG	EE	HG	DC	all	EG	EE	HG	DC
MeD	MULTI-OUTPUT	0.07	71.60	80.20^{+}	69.28	65.32	22.21^{+}	63.09	66.39^{+}	45.50	44.76
	SEPARATE	0.07	70.87	80.24^{+}	68.53	65.80	21.25^{+}	63.15	65.31^{+}	50.26	49.26
	CONCAT	0.06^{+++}	71.05	79.96^{+}	69.36	65.18	23.01^{++}	67.86	66.43^{+}	44.51	45.40
	PREF-BASELINE	0.07	70.02	75.46	69.32	65.74	19.77	52.91	38.87	46.34	49.03
	MAJ-BA									1	1.39
	human up									8	76.50
TeD	MULTI-O									$^{+}$	47.10
	SEPARATE	0.07	76.38	79.47^{+}	57.05	57.52	18.34	54.68	78.89^{+++}	32.09	36.11
	CONCAT	0.06^{++}	78.71^{+}	79.07^{+}	57.12	62.53^{+}	21.68^{+++}	56.75	68.75^{+}	32.51	51.97^{+}
	PREF-BASELINE	0.06	77.60	77.21	55.67	61.02	18.93	57.25	45.15	36.62	49.71
	MAJ-BASELINE	0.11	31.75	23.11	32.03	30.97	4.42	31.21	30.75	32.61	6.28
	human upper bound	0.03	93.29	90.71	81.77	82.11	30.58	78.68	88.99	79.96	95.04

Conclusion: Overlapping segments are highly challenging!

Automatic Detection: Results

Upper Bound: 62.5

$M_A = \textit{macro-F1}(\mathscr{P}(A), \mathcal{X})$

		HL	M_S				M_A	M_O			
	Architecture	all	EG	EE	HG	DC	all	EG	EE	HG	DC
MeD	MULTI-OUTPUT	0.07	71.60	80.20^{+}	69.28	65.32	22.21^{+}	63.09	66.39^{+}	45.50	44.76
	SEPARATE	0.07	70.87	80.24^{+}	68.53	65.80	21.25^{+}	63.15	65.31^{+}	50.26	49.26
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	PREF-BASELINE										49.03
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	human upper bound										76.50
TeD	MULTI-OUTPUT	0.07	78.53	78.87^{+}	57.16	61.77	19.96^{+}	58.42	71.98^{+}	32.61^{+}	47.10
	SEPARATE	0.07	76.38	79.47^{+}	57.05	57.52	18.34	54.68	78.89^{+++}	32.09	36.11
	CONCAT	0.06^{++}	78.71^{+}	79.07^{+}	57.12	62.53^{+}	21.68^{+++}	56.75	68.75^{+}	32.51	51.97^{+}
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	human upper bound	0.03	93.29	90.71	81.77	82.11	30.58	78.68	88.99	79.96	95.04

Conclusion: No architecture wins!

Detecting Diagnostic Reasoning Steps

1) **Corpus Creation**
2) **Automatic Detection**

The patient reports to be lethargic and feverish.
From the anamnesis I learned that he had purulent tonsilitis and is still suffering from symptoms.
I first performed some laboratory tests and notice the decreased number of lymphocytes, which can be indicative of a bone marrow disease or an HIV infection.
The HIV test is positive.
However, the results from the blood cultures are negative, so it is a virus, parasite, or a fungal infection causing the symptoms.

Hypothesis Generation
Evidence Generation
Evidence Evaluation
Drawing Conclusions

Annotating the 2nd half of self-explanations

Schulz, et al. "Analysis of Automatic Annotation Suggestions for Hard Discourse-Level Tasks in Expert Domains."
Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics. 2019.

Extending the Corpus

INCEpTION

The patient reports to be lethargic and feverish.
From the anamnesis I learned that he had purulent tonsilitis and is still suffering from symptoms.
I first performed some laboratory tests and notice the decreased number of lymphocytes, which can be indicative of a bone marrow disease or an HIV infection.
The HIV test is positive.
The blood cultures are negative, so it is a virus, which is the infection causing the symptoms.

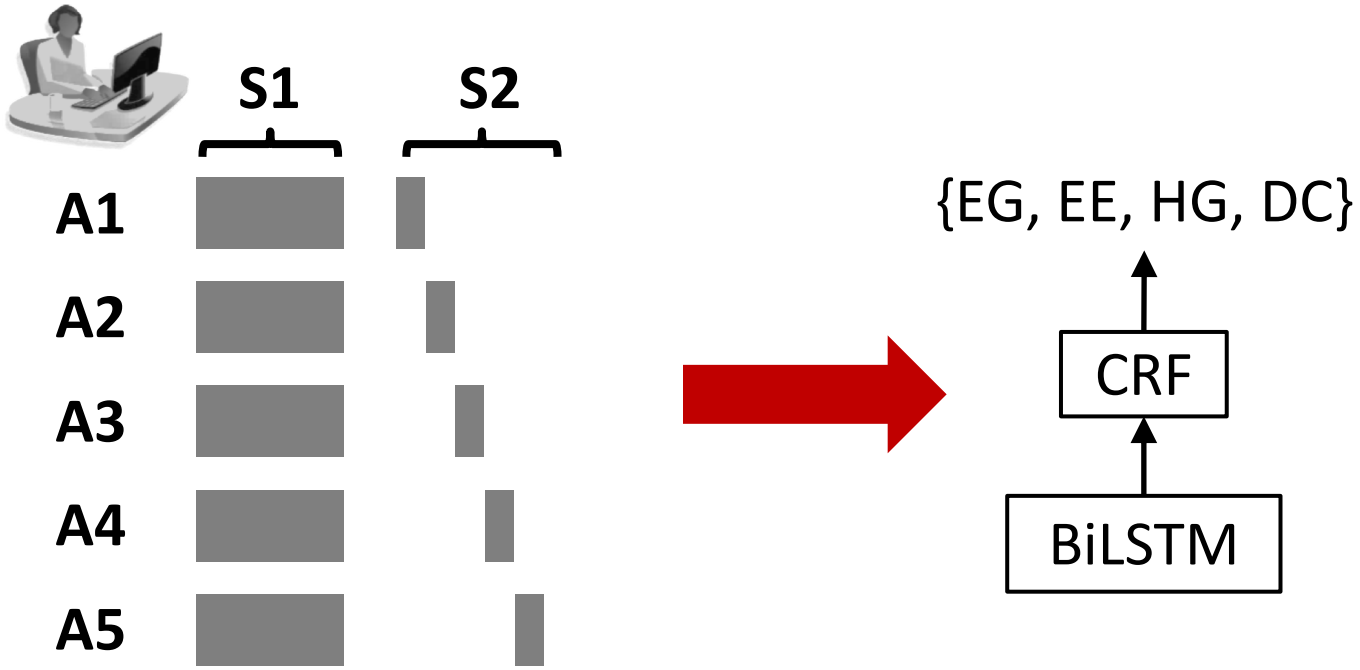
Suggestion:
Hypothesis generation (HG)

✓ Accept ✗ Reject

predictions
(PREF-BASELINE)

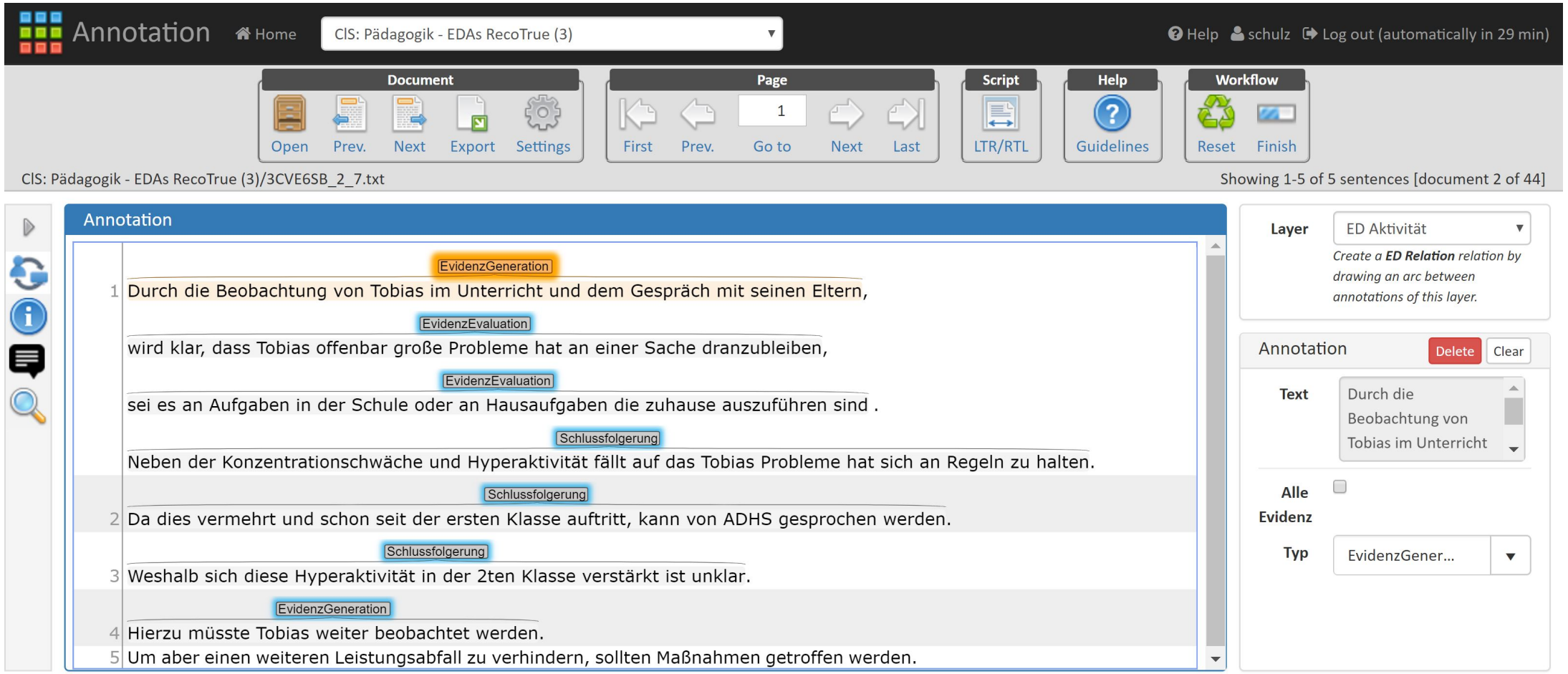
Hypothesis Generation
Evidence Generation
Evidence Evaluation
Drawing Conclusions

Training Data and Suggestion Quality

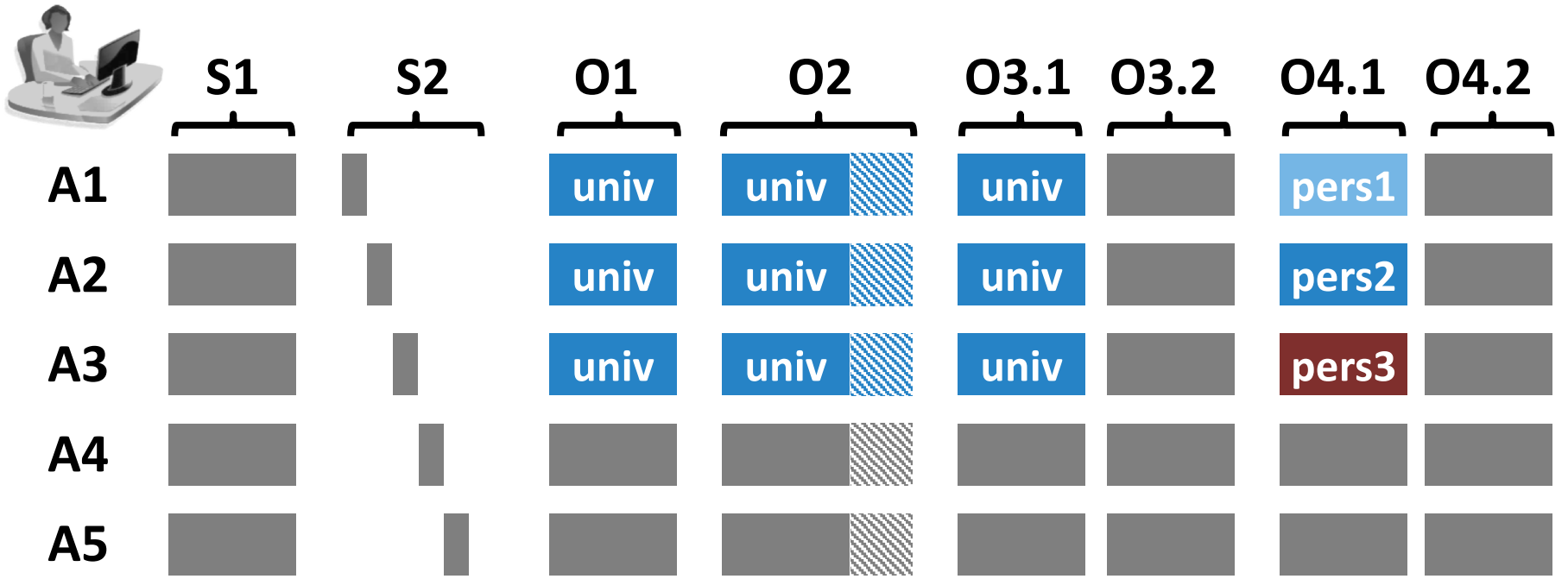


univ(ersal) model: $F_1 \approx .63$
pers(onalized) models: $F_1 \approx .55$

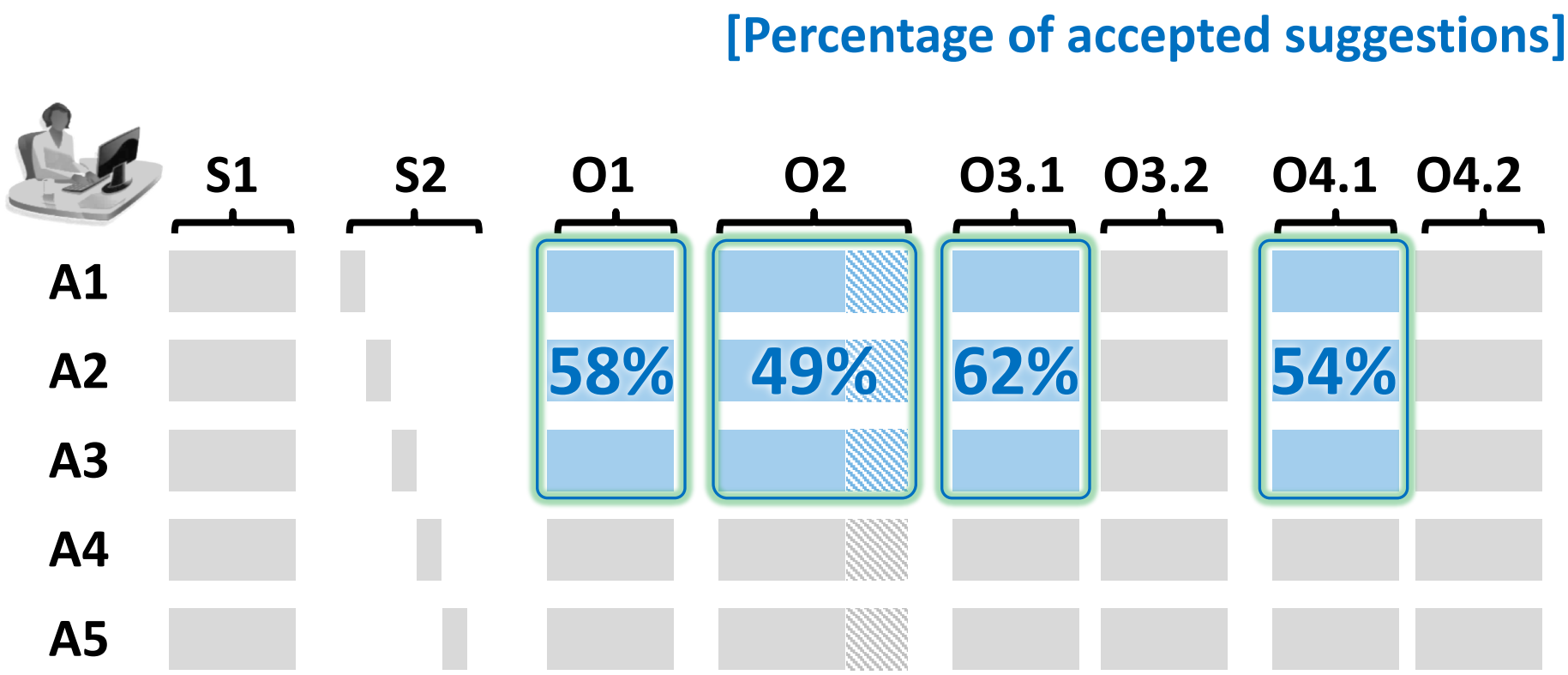
Annotation Suggestions in INCEpTION



Annotation Suggestions - Setup

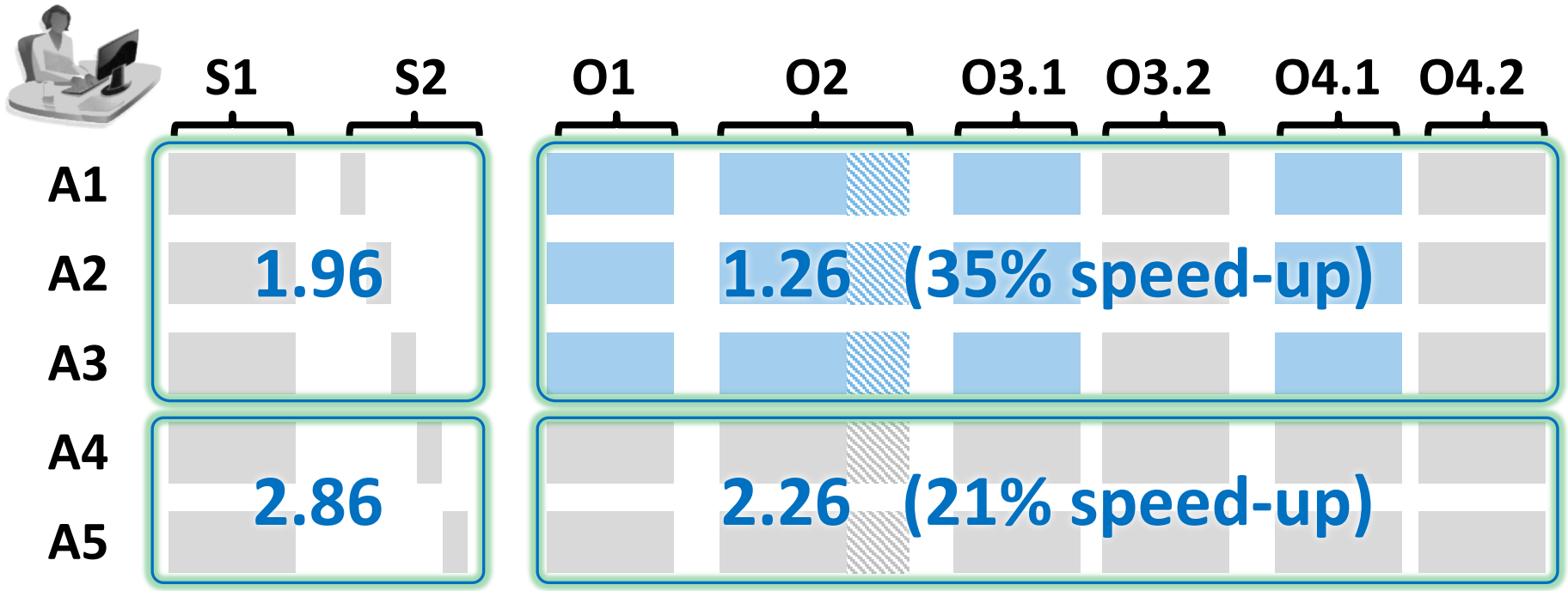


Usefulness of Annotations



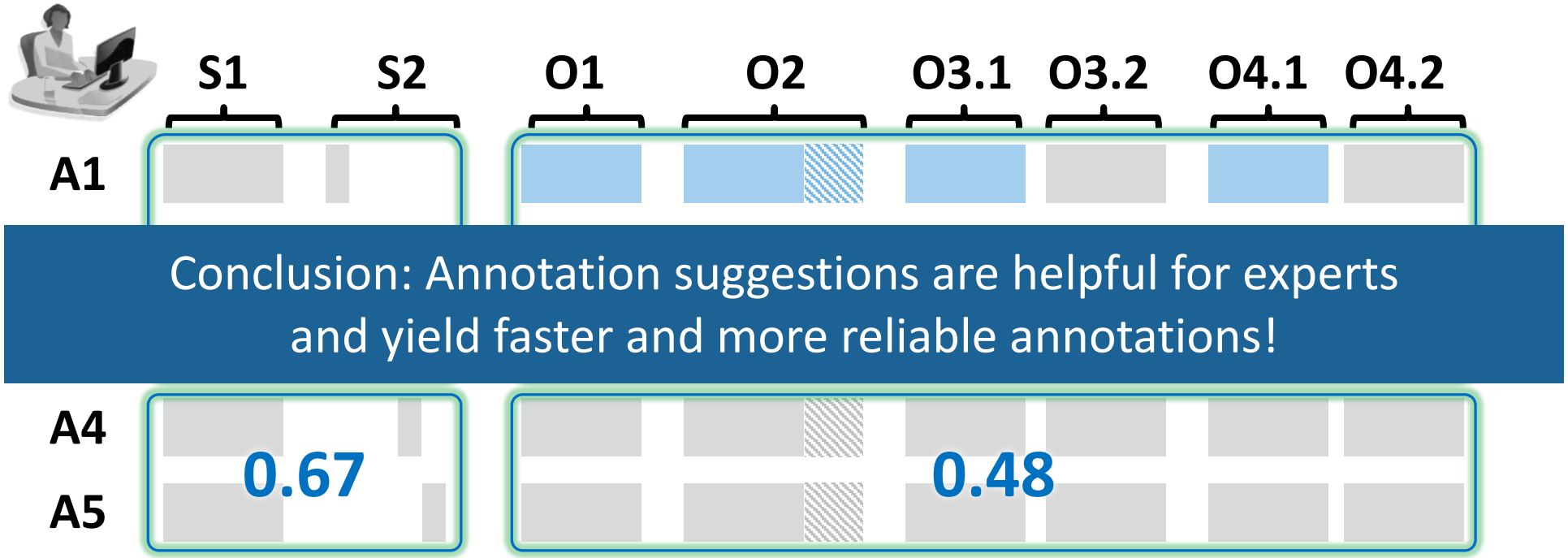
Annotation Time

[Minutes per text]



Reliability of Annotations

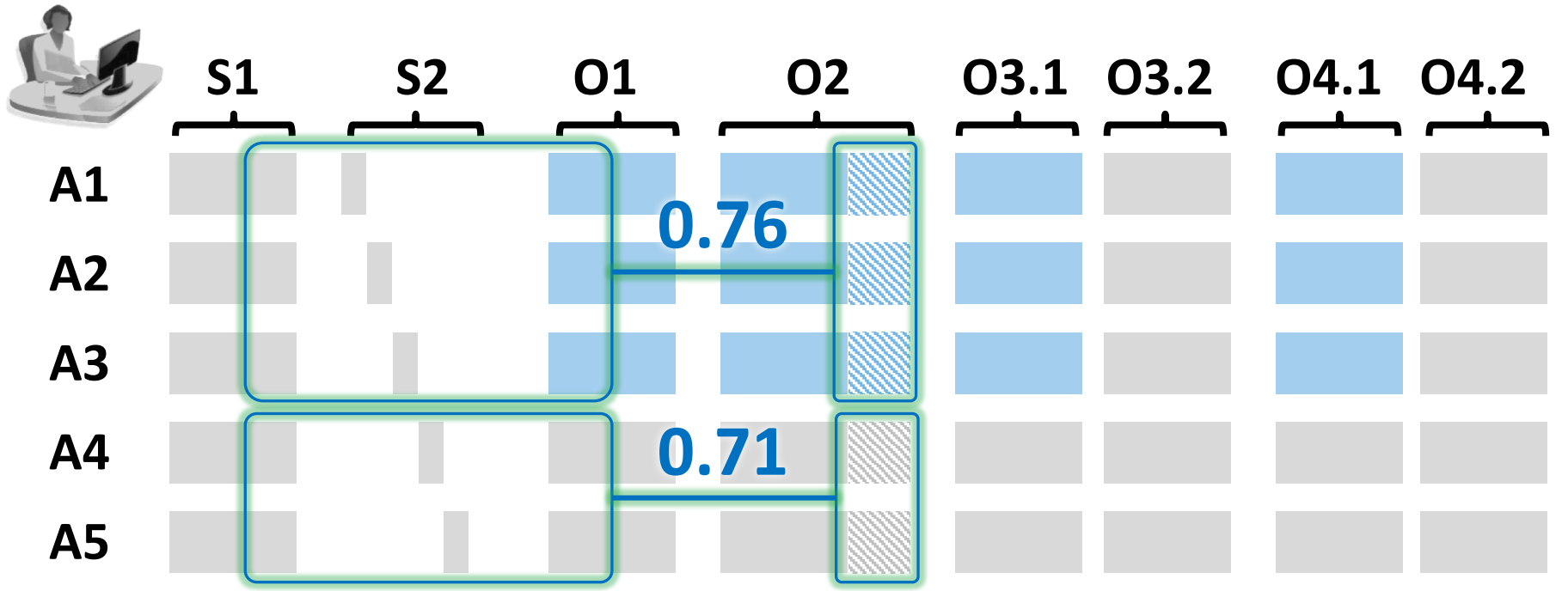
[Krippendorff's α]



Conclusion: Annotation suggestions are helpful for experts and yield faster and more reliable annotations!

Intra-Annotator Consistency

[Krippendorff's α]



Human / Suggestion Model Agreement

[Krippendorff's α]

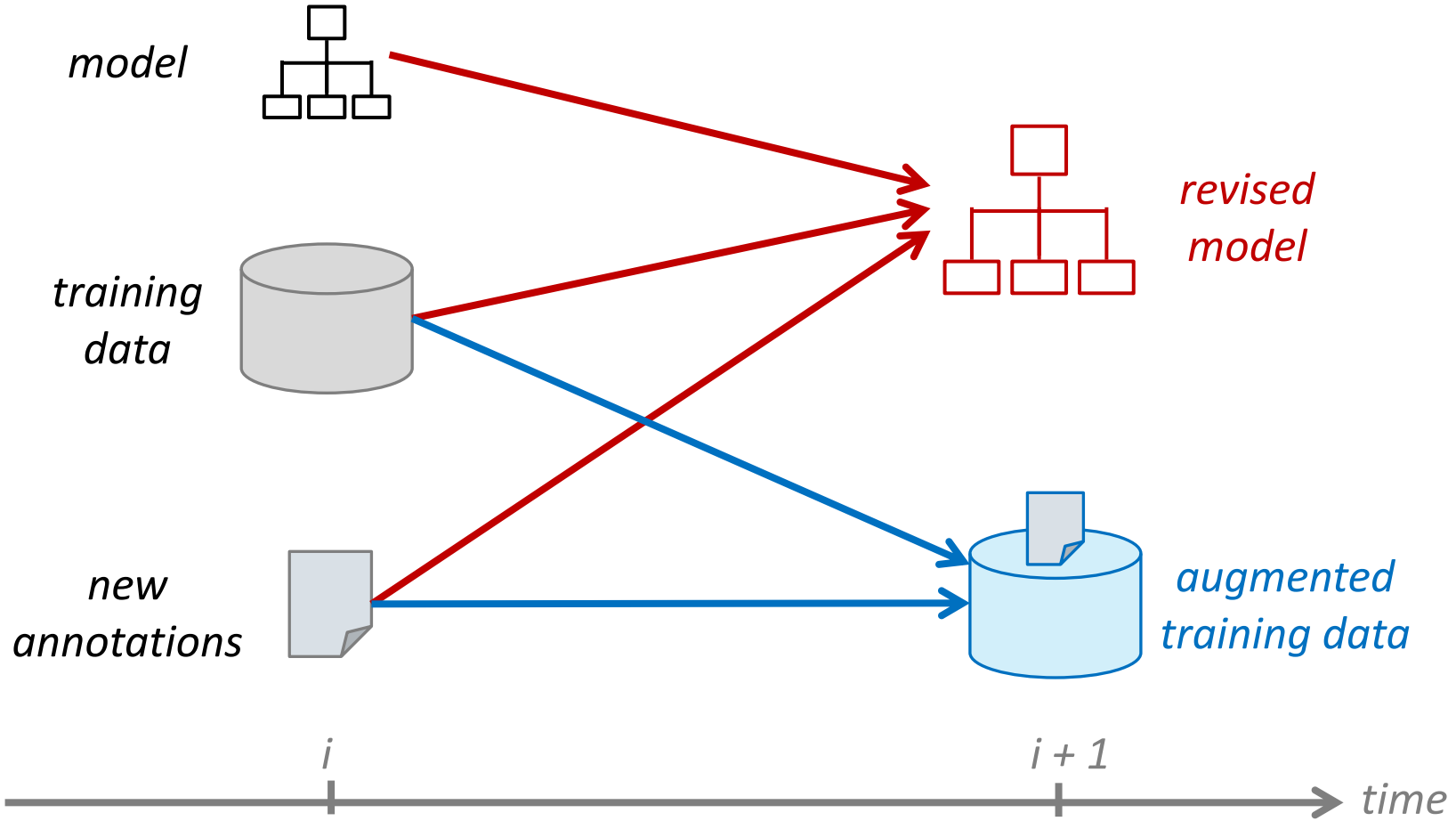
	S1	S2	O1	O2	O3.1	O3.2	O4.1	O4.2
A1								
A4			0.56	0.48	0.55		0.30	
A5								

Conclusion: Some evidence for annotation bias, but negligible, as no systematic discrepancy compared to the control setup!

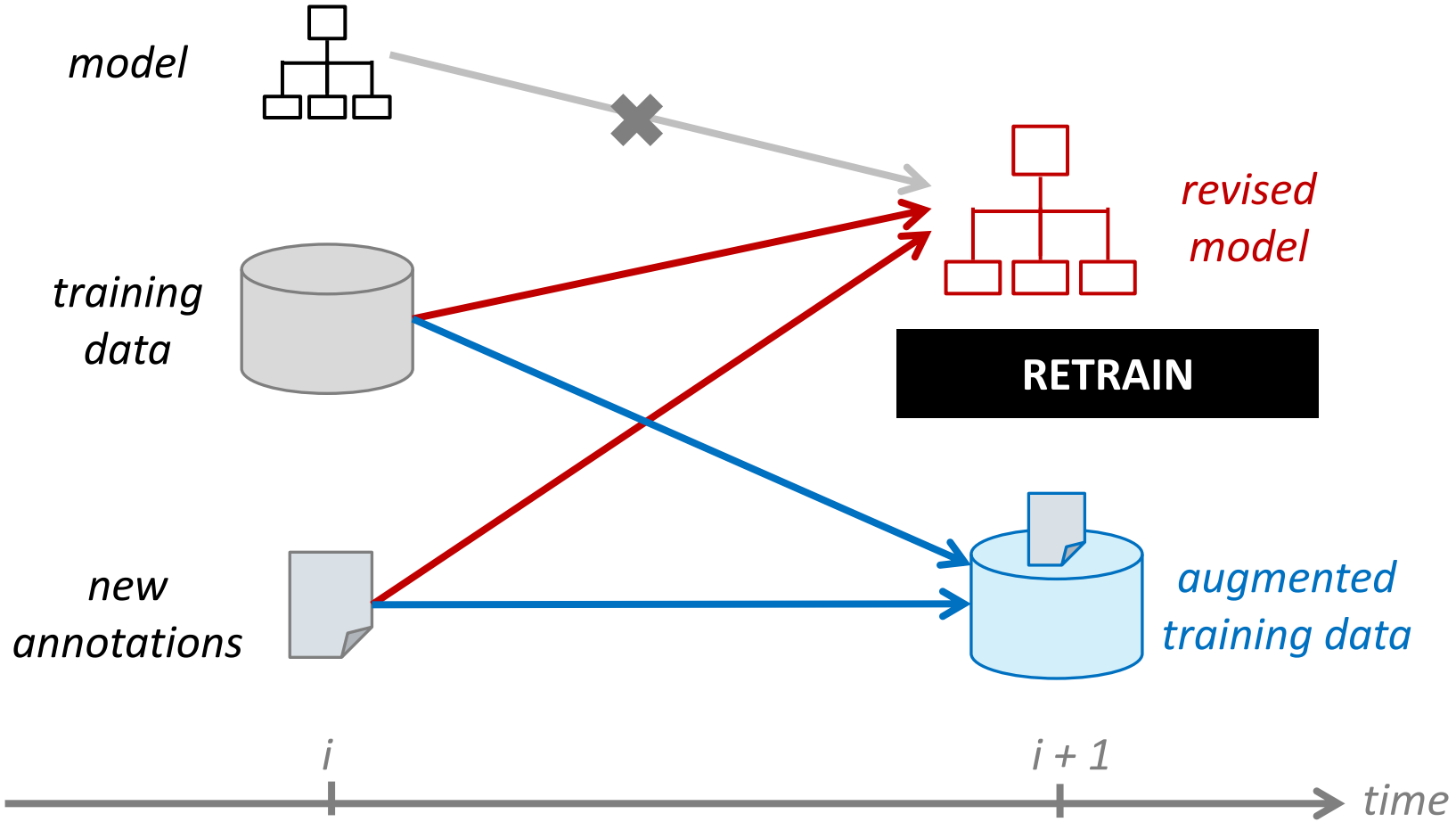
Iterative Model Training

Schulz, et al. "Analysis of Automatic Annotation Suggestions for Hard Discourse-Level Tasks in Expert Domains."
Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics. 2019.

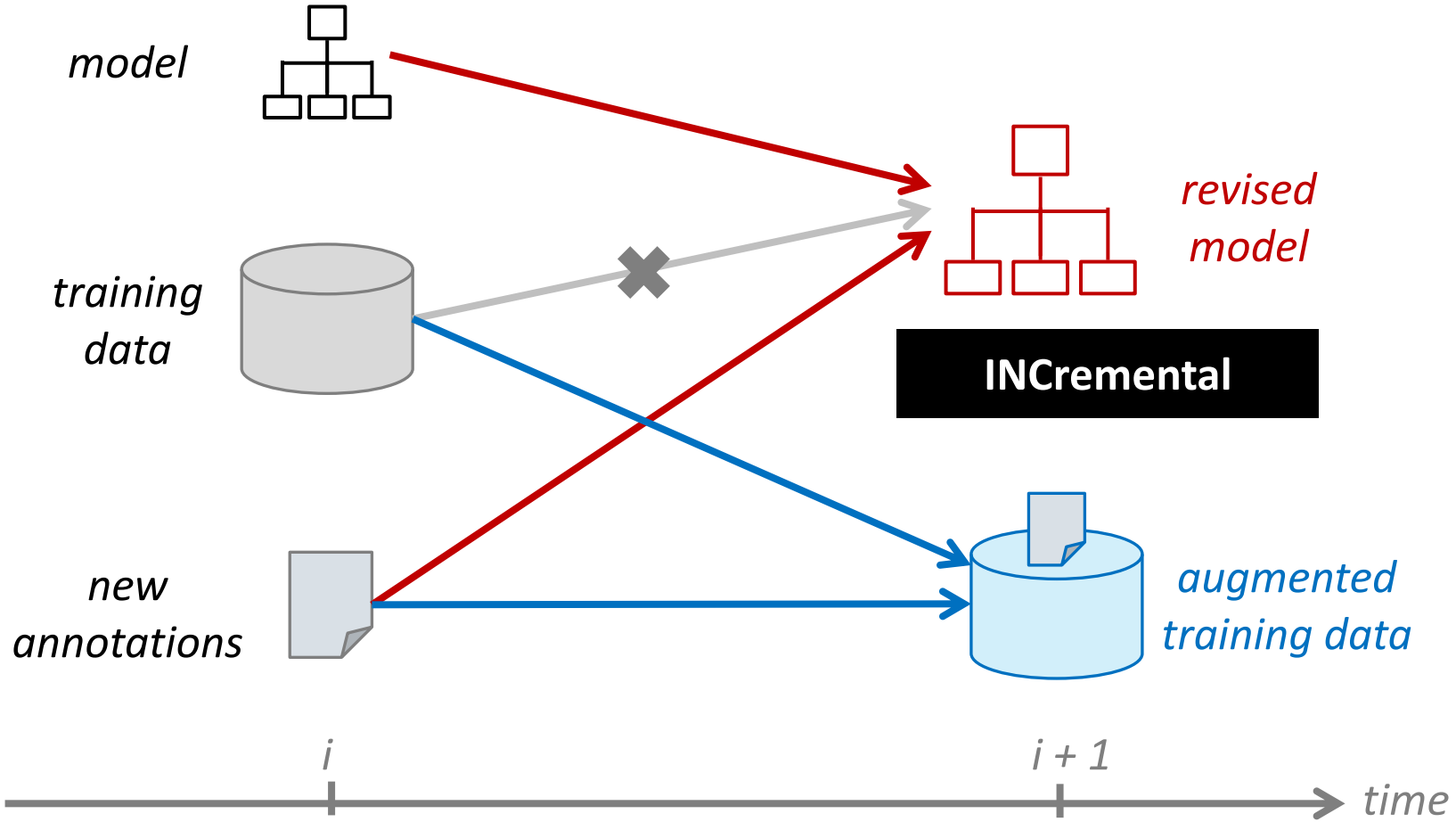
Iterative Model Training



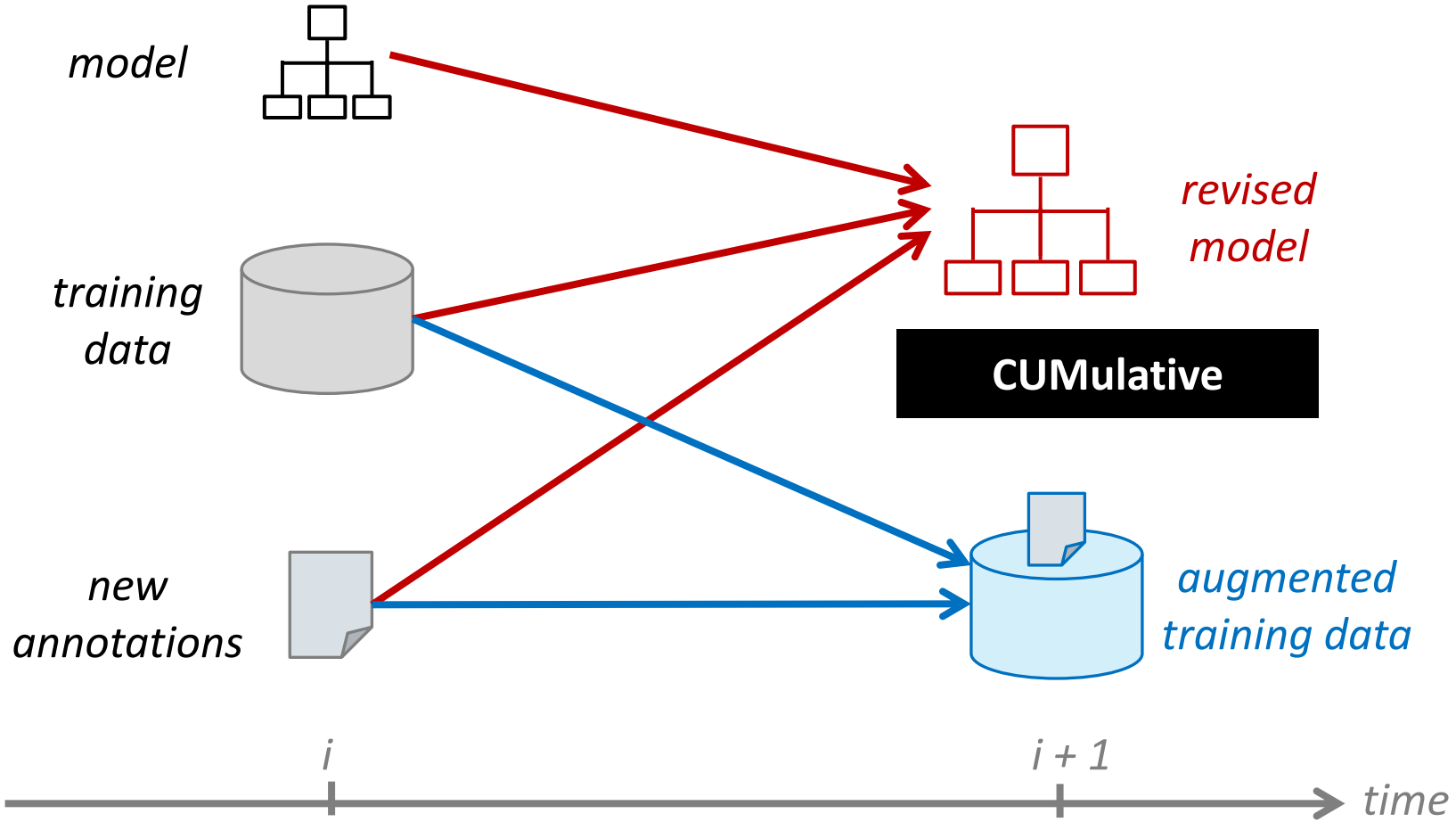
Iterative Model Training



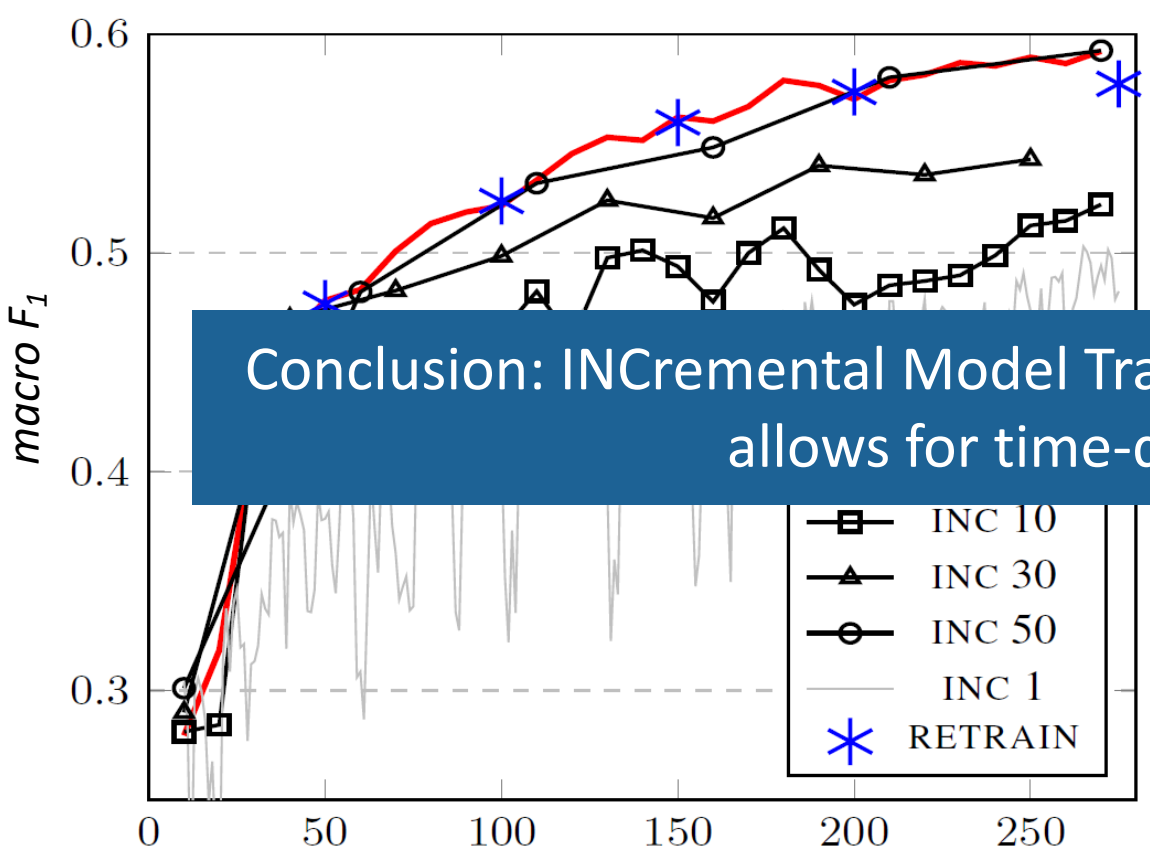
Iterative Model Training

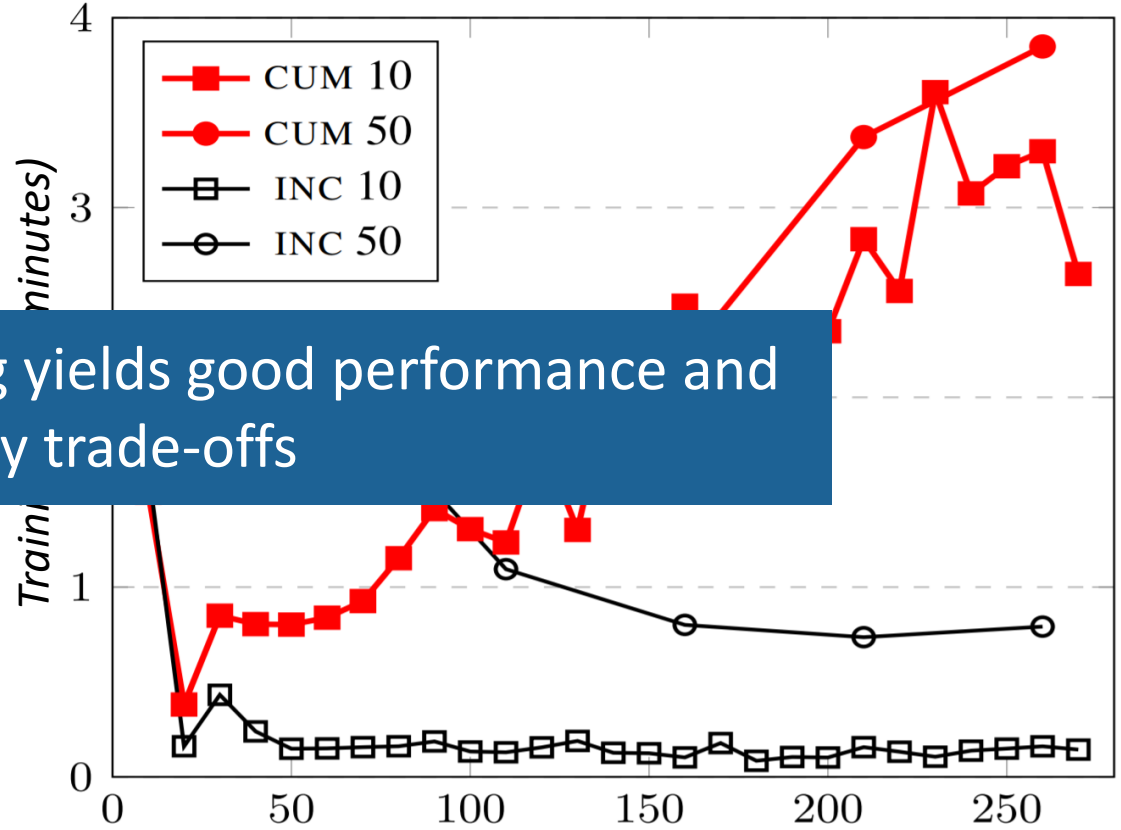


Iterative Model Training



Model Performance





Conclusion: INCremental Model Training yields good performance and allows for time-quality trade-offs

training data (no of texts)

Automatic Feedback on Diagnostic Reasoning

Detecting Diagnostic Reasoning Steps

1) **Corpus Creation**
2) **Automatic Detection**

The patient reports to be lethargic and feverish.
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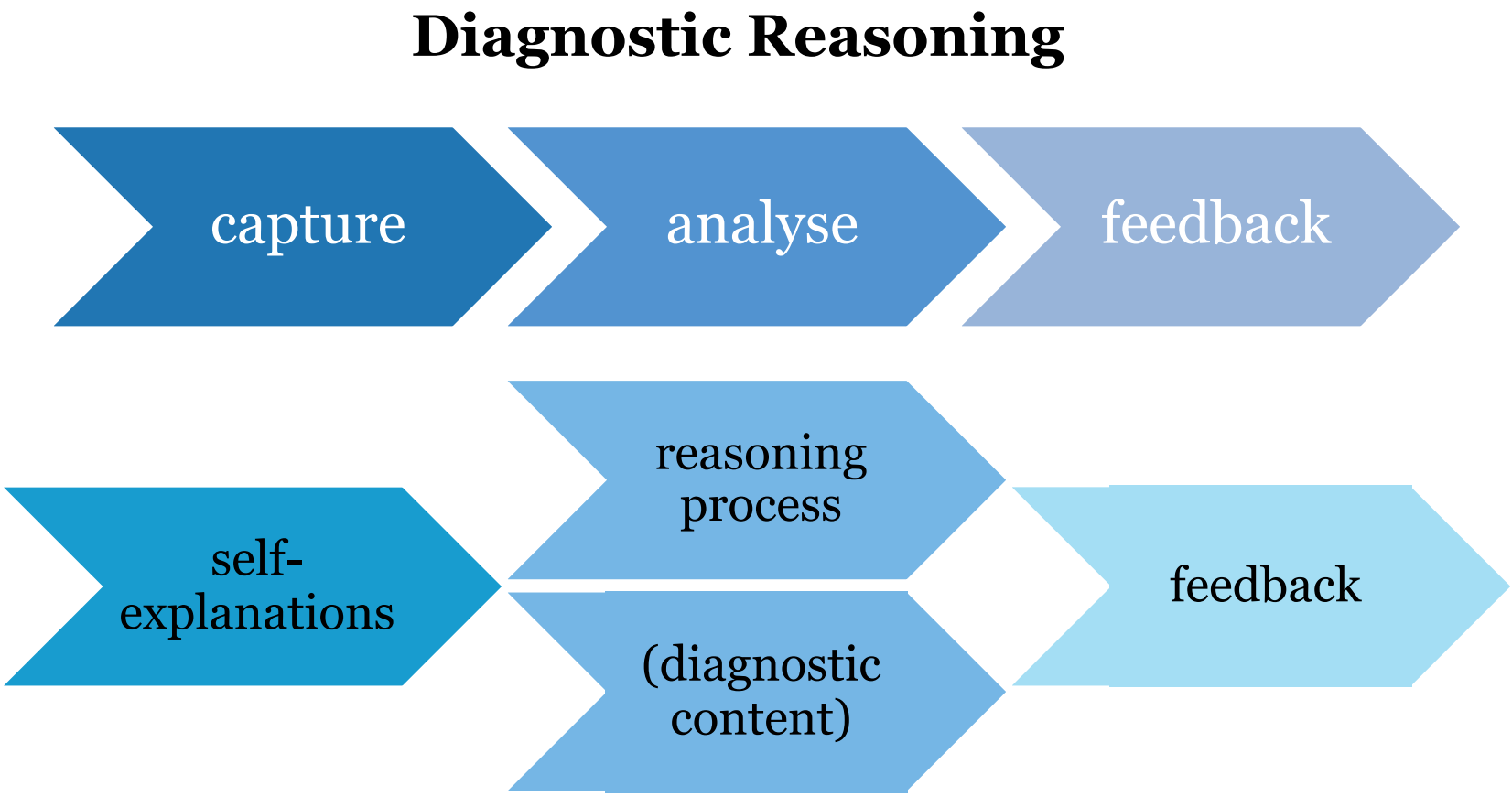
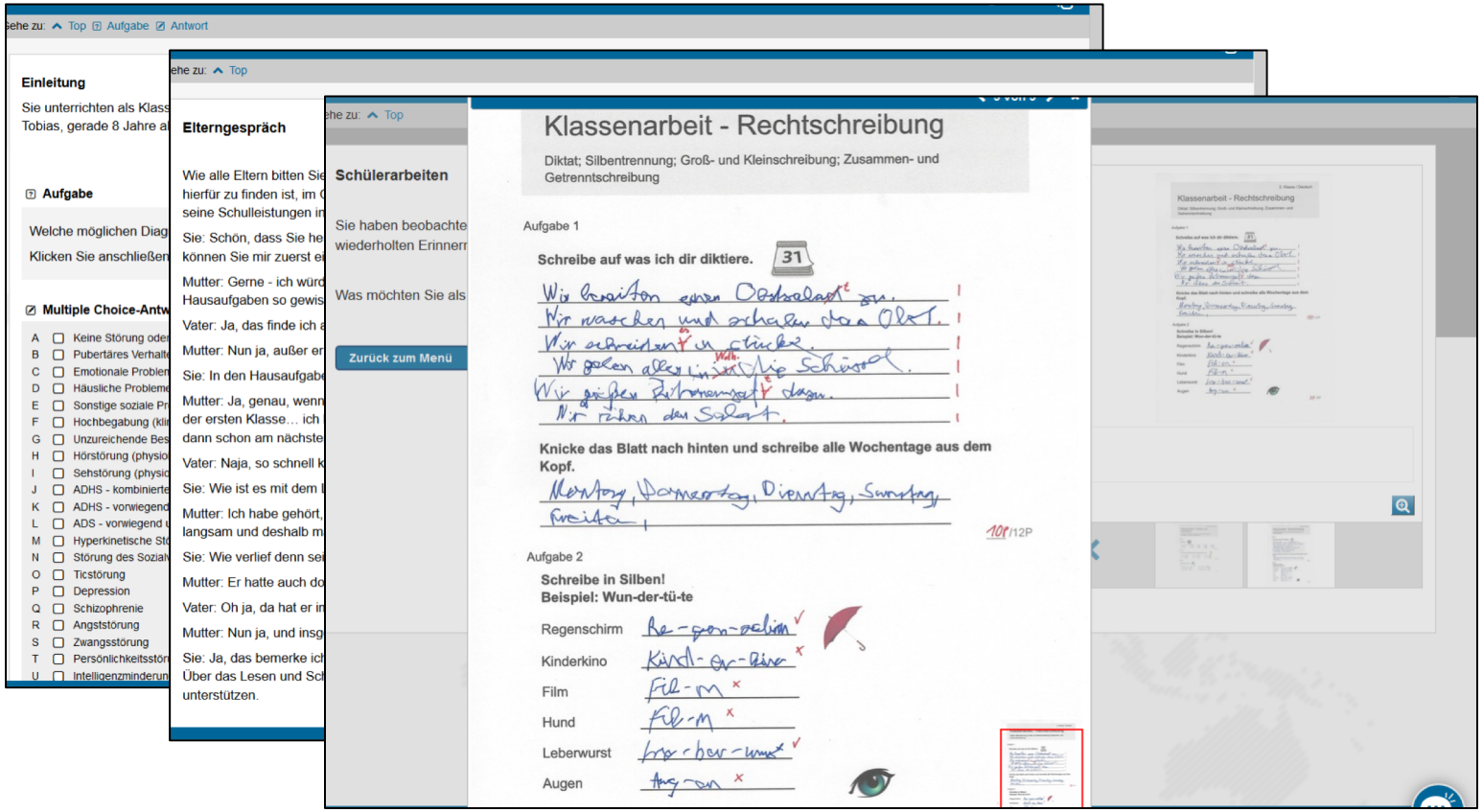
However, the results from the blood cultures are negative, so it is a virus, parasite, or a fungal infection causing the symptoms.

Hypothesis Generation
Evidence Generation
Evidence Evaluation
Drawing Conclusions

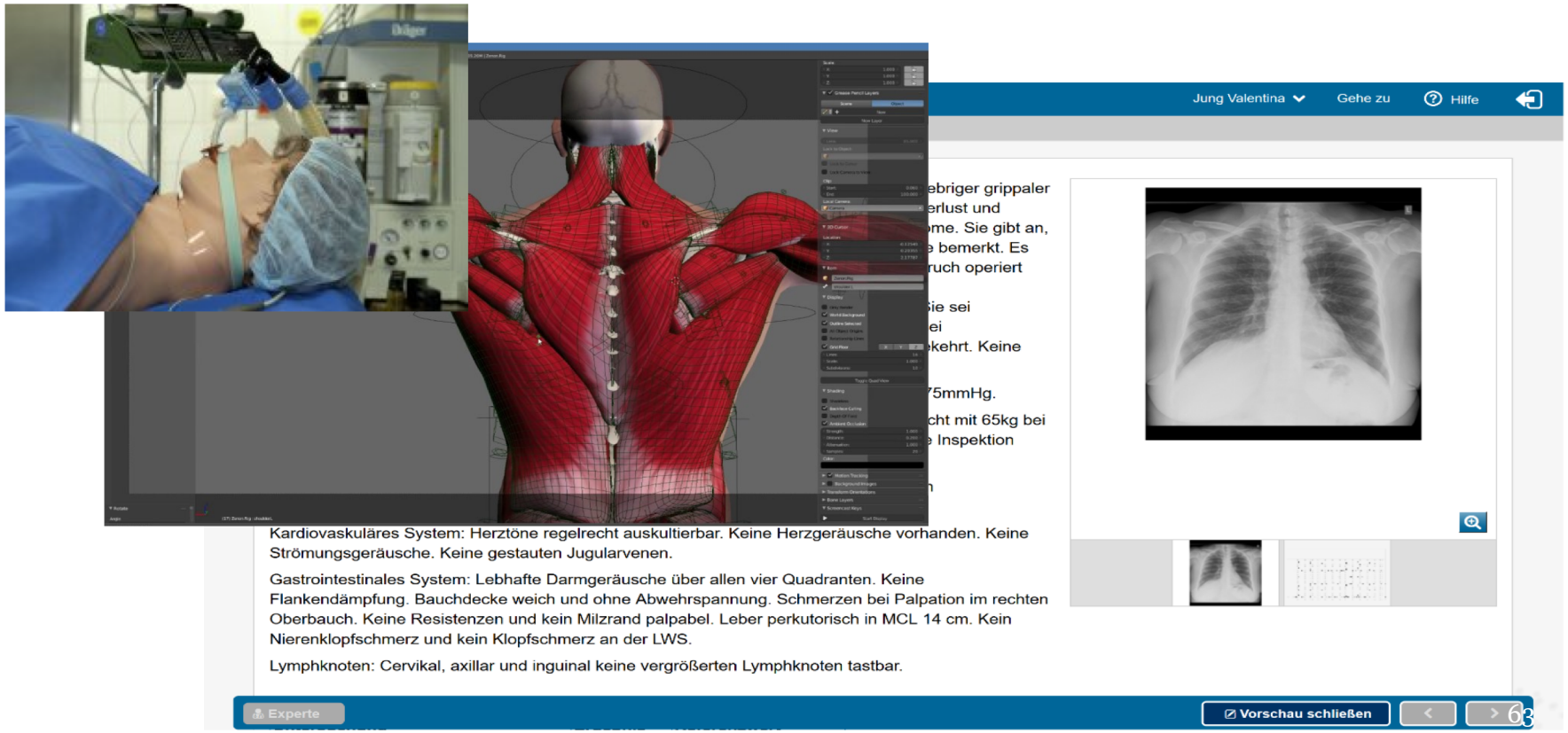
Adaptive Feedback



eLearning Platform CASUS®

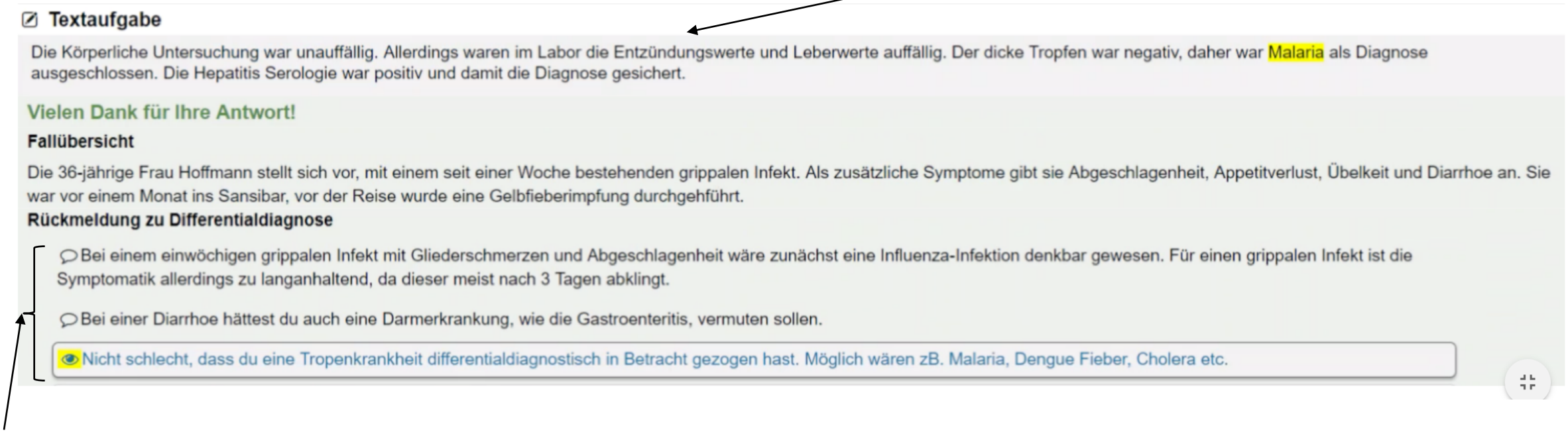


eLearning Platform CASUS®

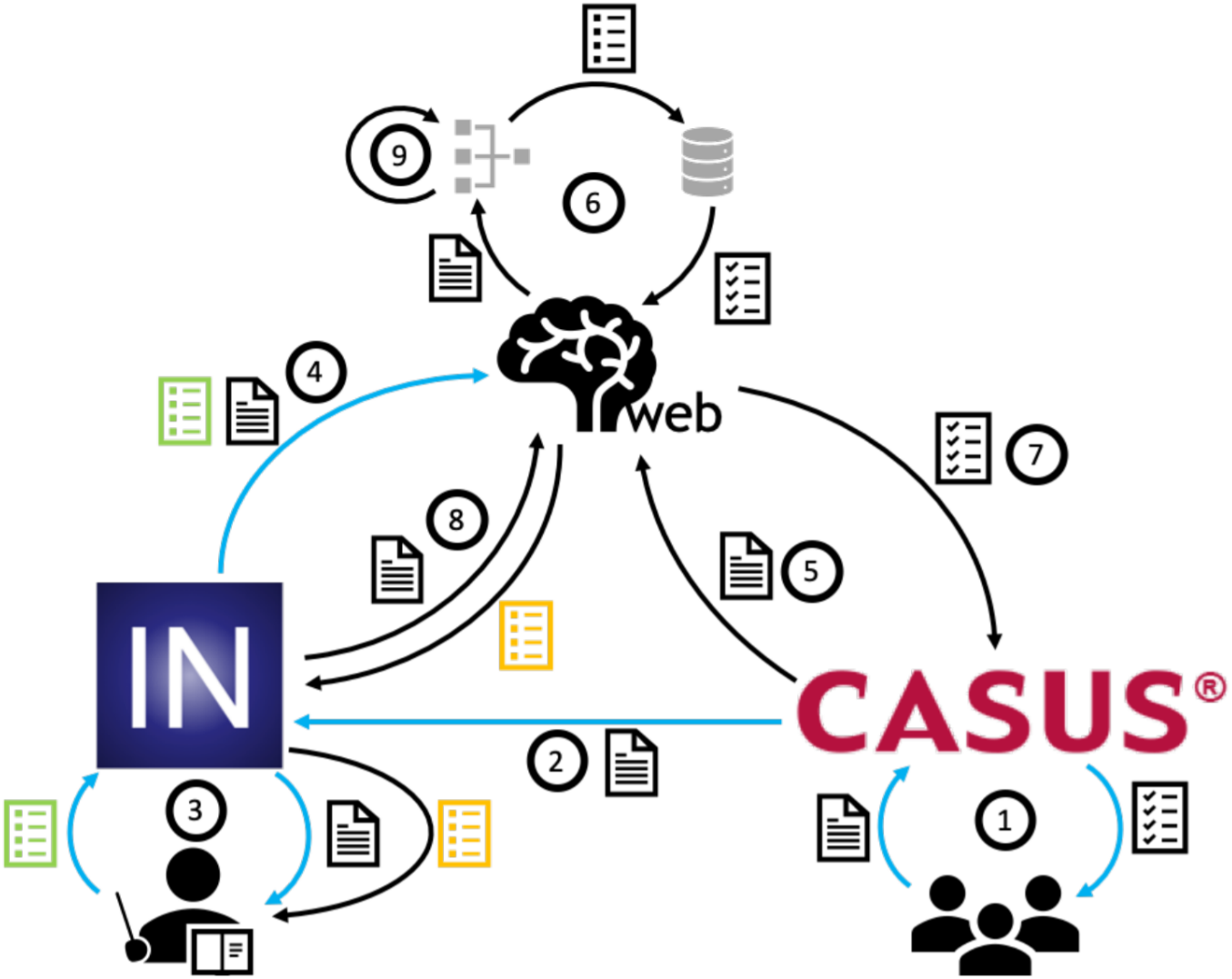


Automatic Feedback

student's self-explanation



automatic adaptive feedback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Wrapping Up

Explaining how to improve Diagnostic Reasoning

- Collect Self-Explanations
- Annotate Diagnostic Reasoning Steps
  - Train model for annotation suggestions → ease and speed-up
- Train Model for Detecting Reasoning Steps
- Use Model for Automatic Feedback

My publications
http://www.famulus-project.de/
https://inception-project.github.io/

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