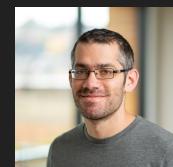




# Process-Level Representation of Scientific Protocols with Interactive Annotation

Ronen Tamari, Fan Bai, Alan Ritter, Gabriel Stanovsky



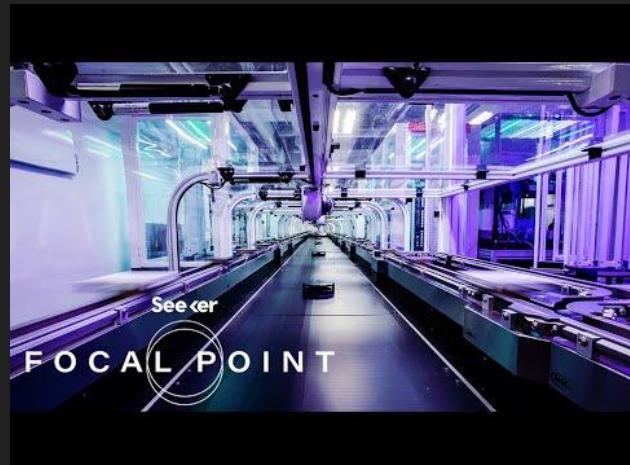
# Motivation

- > Scientific literature contains millions of unstructured natural language texts describing experimental material synthesis procedures (“recipes”)
- > Vast potential for data-driven research
- > To date, methods have focused on text-mining applications



# The next frontier: digital synthesis

- > Serious reproduceability concerns have raised the bar
- > The next frontier: convert textual descriptions to automated execution of experimental procedures!



Strateos cloud laboratory

# The next frontier: digital synthesis

- > Serious reproduceability concerns have raised the bar
- > The next frontier: convert textual descriptions to automated execution of experimental procedures!



Prof. Lee Cronin @leecronin · Oct 5

By digitising synthesis we will be able share failed as well as successful procedures, & be able to collaborate widely - perhaps sharing a working synthesis on a repo before the publication. Maybe validation of the 'synthesis code' could be required before publication 4/5

1 reply · 1 retweet · 19 likes

# Text-to-experiment

- > Objective: parse texts into structured format for integration into automated workflows
- > Poses formidable challenges for current natural language understanding (NLU) systems:
  - Meaning representation (semantics)
  - Annotation
  - Modelling
  - Evaluation

# Text-to-experiment

- > Objective: parse texts into structured format for integration into automated workflows
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  - Modelling
  - Evaluation

# Why rethink semantics?



Can we just use text mining approaches?

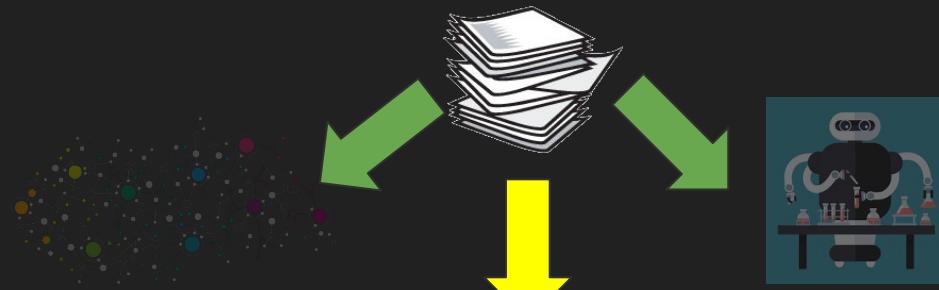
“Although [text mining] approaches are useful for mining literature [...], we need a system that could output a machine-readable representation of a procedure with **sufficient process details to unambiguously execute the procedure on an automated platform**. This **goes beyond simply tagging chemical entities found in literature procedures**”

Can we just parse directly into robot instructions?

“Automated platforms from different companies or research groups all have bespoke instruction sets **with no obvious semantic link among them or to the literature**. This broken link has prevented the digitization of chemistry”

(Mehr et. al, 2020)

# Why rethink semantics?



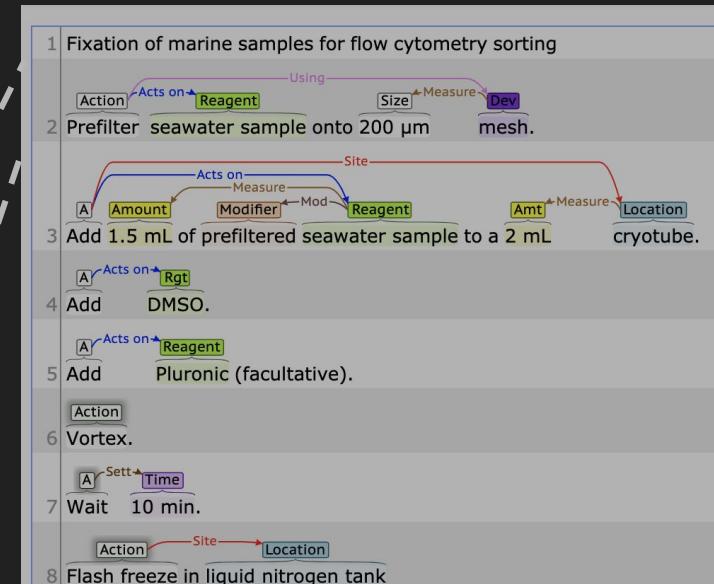
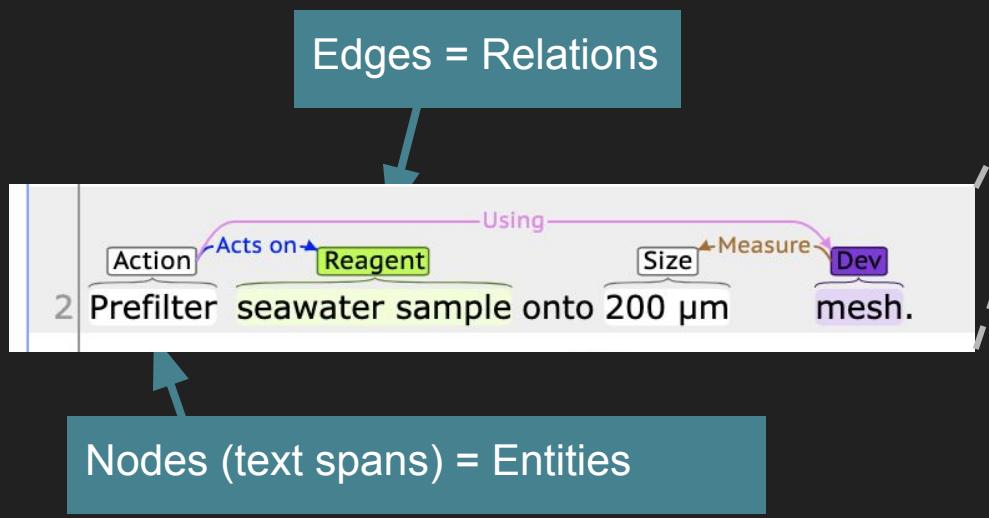
Can we just use text  
mining approaches?

Hardware-agnostic  
representation as scaffold  
for execution

Can we just parse directly  
into robot instructions?

# Text-mining approaches

- > Action-graph semantics: shallow, sentence-level annotations
  - Biology: Wet Labs Protocols (WLP, Kulkarni et. al, 2018) - 622 documents
  - Materials science: Materials Science Procedural Text Corpus (MSPTC, Mysore et. al, 2019) - 230 documents



WLP instance

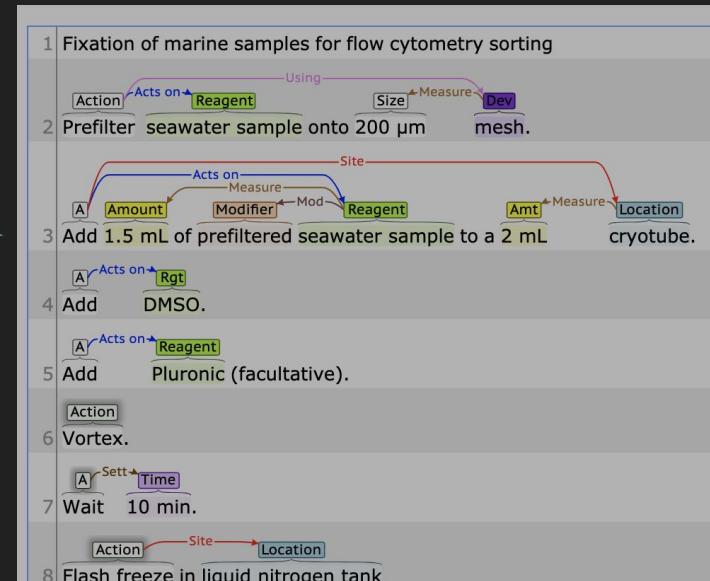
# Text-mining approaches

- > Action-graph semantics: shallow, sentence-level annotations
  - Biology: Wet Labs Protocols (WLP, Kulkarni et. al, 2018) - 622 documents
  - Materials science: Materials Science Procedural Text Corpus (MSPTC, Mysore et. al, 2019) - 230 documents

Complex texts, require expert & common-sense knowledge



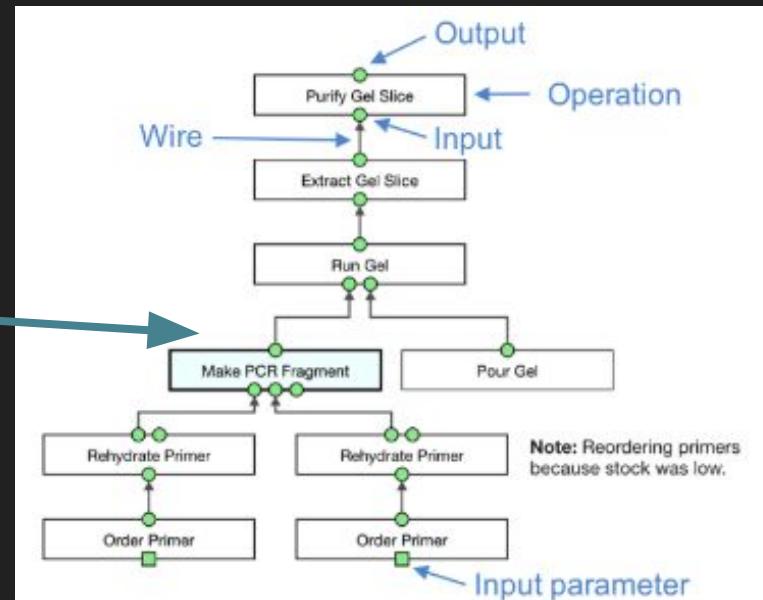
WLP instance



# What's missing?

- > Inspiration from executable biology protocols research
- > Protocols as:
  - Computation graphs

Process-level representation:  
connected graph tracking  
operation inputs and outputs



Aquarium (Keller et. al, 2019)

# What's missing?

- > Inspiration from digital synthesis research
- > Protocols as:
  - Computation graphs
  - Sequence of API calls

Typed operations

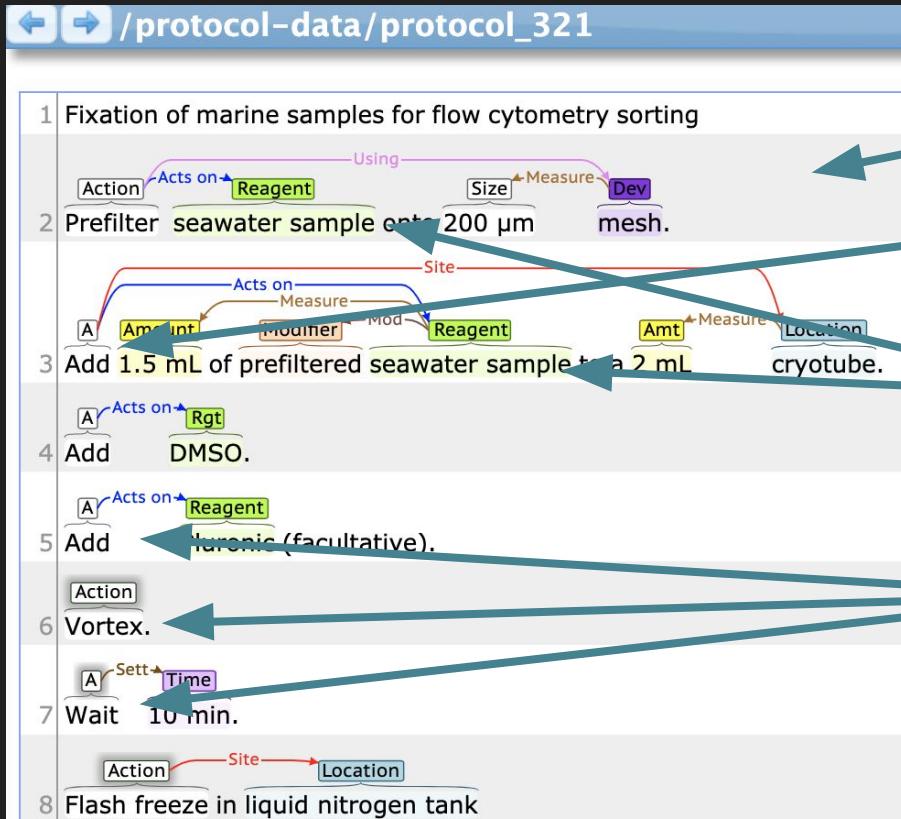
References as persistent objects rather than text spans

```
# transfer the first primer
protocol.transfer(params.primer_pairs[0][0], params.taq_tubes[0],
                  params.primer_vol_total)
# transfer the second primer and mix the solution
protocol.transfer(params.primer_pairs[0][1], params.taq_tubes[0],
                  params.primer_vol_total,
                  mix_after=True, mix_vol=params.primer_vol_total,
                  repetitions=5)
# distribute the master mix from the first Taq tube to the first
# quadrant of the PCR plate, mix before aspirating the solution
protocol.distribute(params.taq_tubes[0], dest_plate.quarter(0),
                     params.mm_vol,
                     allow_carryover=True, mix_before=True,
                     mix_vol=params.primer_vol_total, repetitions=4)

# add the DNA from the 96-well plate to the first quadrant and mix
protocol.stamp(params.dna_plate, dest_plate, 0, params.dna_vol,
               mix_after=True, mix_vol=params.dna_vol, repetitions=3)
# seal and thermocycle
protocol.seal(dest_plate)
protocol.thermocycle(dest_plate, [{
```

Autoprotocol (Lee & Miles, 2018)

# Action-graphs: limitations



Sentence-level annotations

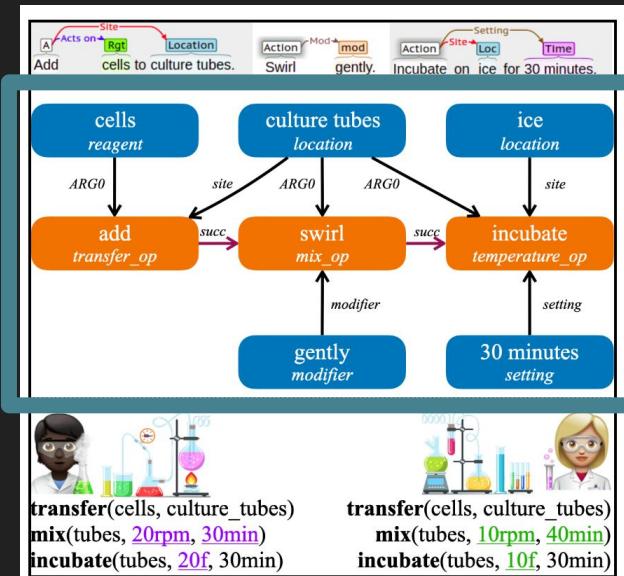
Missing fine-grained action types

References not persistent beyond sentence

Implicit arguments

# Our proposal: Process Execution Graphs (PEG)

- > Process-level abstract executable representation
- > Bridges between procedural text and downstream automated workflows



# PEG: Definitions

- > Directed, a-cyclic labeled graph
- > Ontology based on Autoprotocol

## BACKGROUND

Motivation

Design Goals

Conventions

## PROTOCOLS

Structure

Aliquot Paths

## DEFINITIONS

Types

Units

Fields

## REFS

container\_refs

## INSTRUCTIONS

acoustic\_transfer

cover

flow\_cytometry

incubate

liquid\_handle

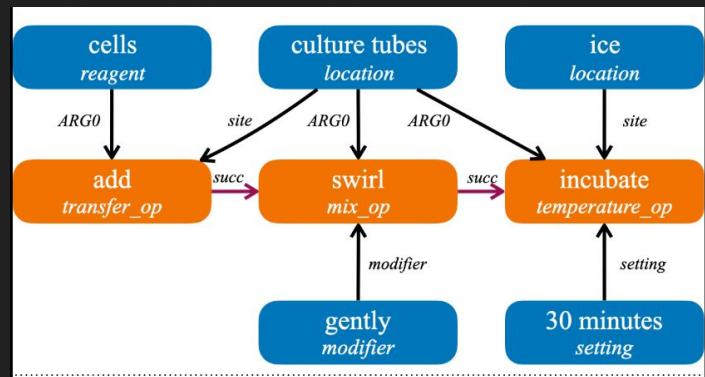
measure\_mass

measure\_volume

provision

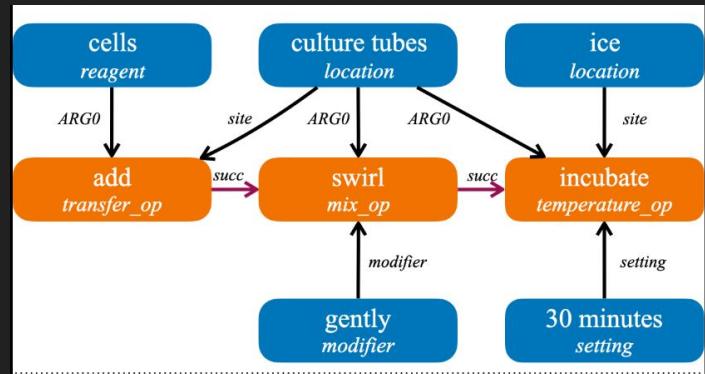
# PEG: Definitions

- > Directed, a-cyclic labeled graph
- > Ontology based on Autoprotocol
- > Nodes
  - Predicates (**mix**, **transfer**)
  - Arguments
    - Physical lab entities (device, reagent, etc)
    - Abstract entities like amounts or modifiers



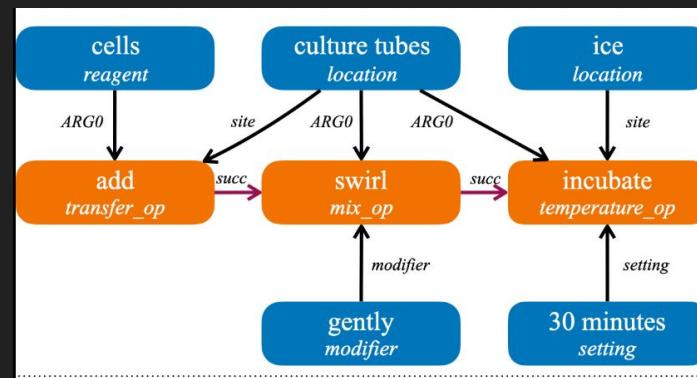
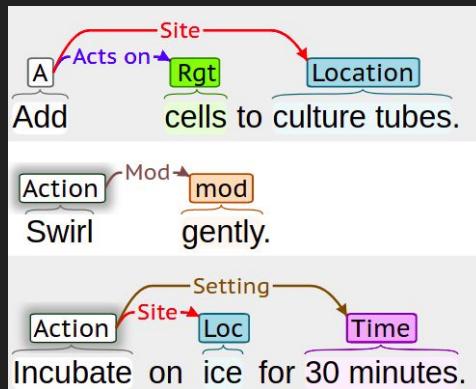
# PEG: Definitions

- > Directed, a-cyclic labeled graph
- > Ontology based on Autoprotocol
- > Edges
  - Core-roles (~positional arguments)
  - Non-core roles (predicate agnostic)
  - Temporal dependency relation



# Comparison with action-graphs

- > Fine-grained operation types
- > Cross-sentence relations
- > Argument re-use: arguments can be persistent objects
- > Enforcing required arguments

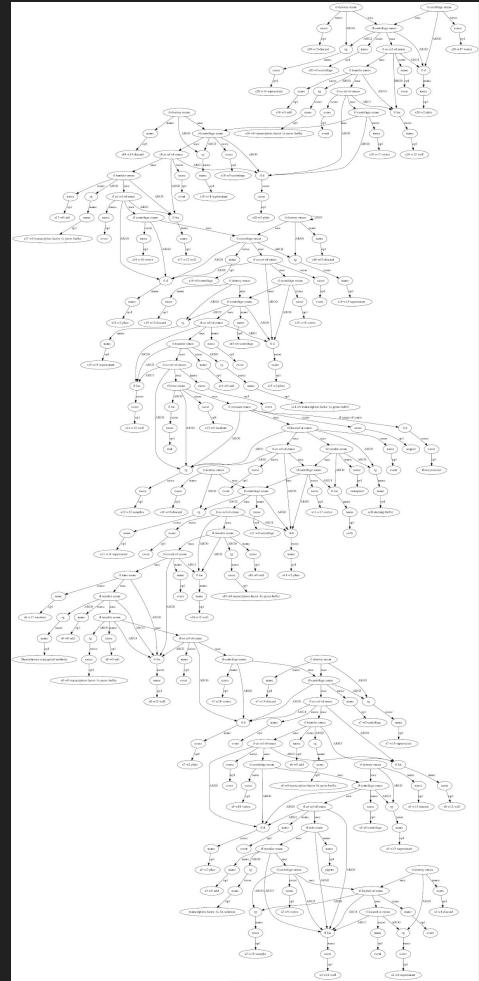


# Annotation interface desiderata

- > Predicate specific execution semantics  
(container moves -> containee moves)
- > Tracking temporal dependencies and entity states over long texts
- > Argument validation

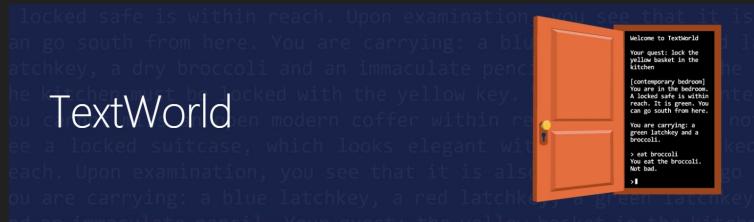
Too complex for span-based annotation!

PEG visualization in AMR using AMRICA (Safra & Lopez, 2015)

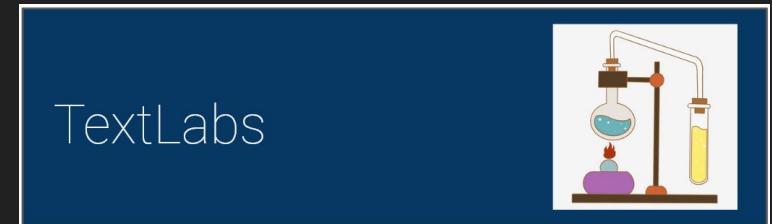


# Text-based games as annotation interface

- > Convenient platform providing cheap interface
- > Suited for tracking and representing dynamic world state
- > We'll adapt it for annotation, too!



(Côté et al, 2018)



(Tamari et al, 2019)

# Text-based games as intuitive annotation interface?

- > Procedures most naturally thought of as sequential execution
- > “Questification”: maybe grounded annotations are easier for humans (and machines)?

Mark O. Riedl  
@mark\_riedl

Replying to [@mark\\_riedl](#)

In text games we call these things quests. Everything is a quest. It's fun to call everything a quest in the real world too.

# Creating the dataset: eXecutable WLP (X-WLP)

- > Pre-populate PEGs with WLP entities and subset of within-sentence relations
- > Annotators enrich them by adding:
  - Type grounding
  - Argument labelling
  - Execution dependencies
  - Cross-sentence relations

# PEG annotation process

- > Annotators interact with text-based game engine
- > Engine ensures semantic validity
- > Further provided assistance:
  - “Linter” for type checking
  - Autocomplete
  - Simple scoring to encourage annotating connected graphs

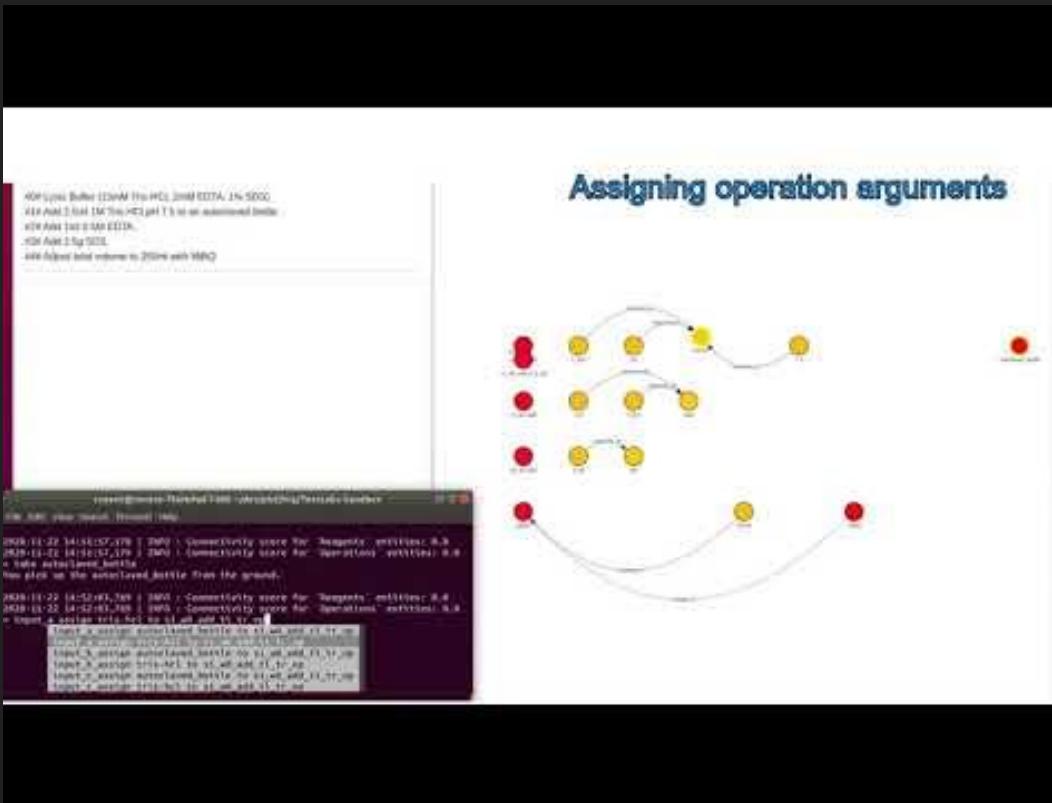
```
> op_type incubate to temp_type
Set operation type!

> op_run incubate
Failed: missing "ARG0" input for incubate!

> take culture_tubes
You pick up the culture_tubes.

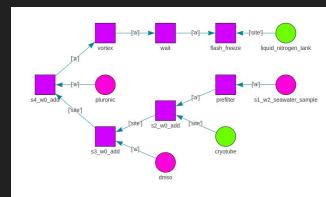
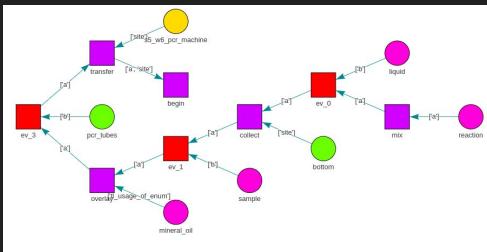
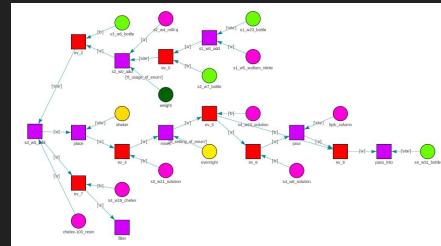
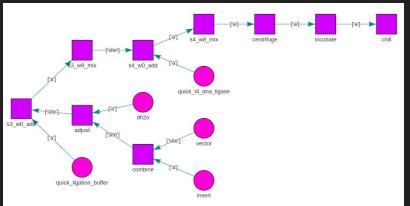
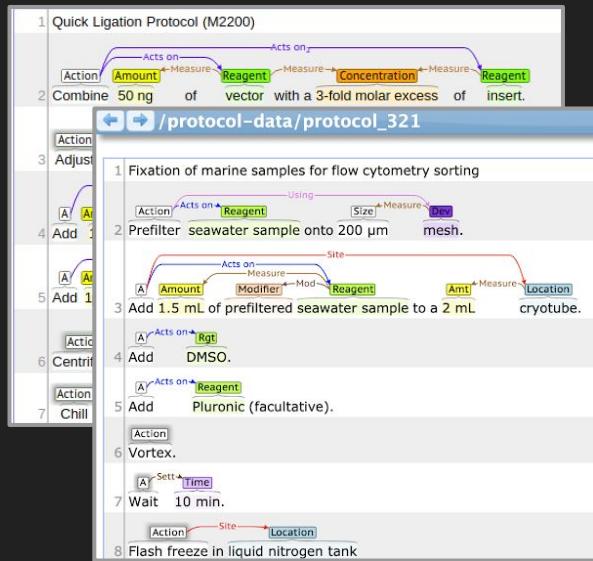
> ARG
    ARG0_assign culture_tubes to incubate
    ARG1_assign culture_tubes to incubate
    ARG2_assign culture_tubes to incubate
```

# Demo



# X-WLP stats

> 3 annotators, enriched 279/622 (45%) WLP protocols to PEG format



## X-WLP stats

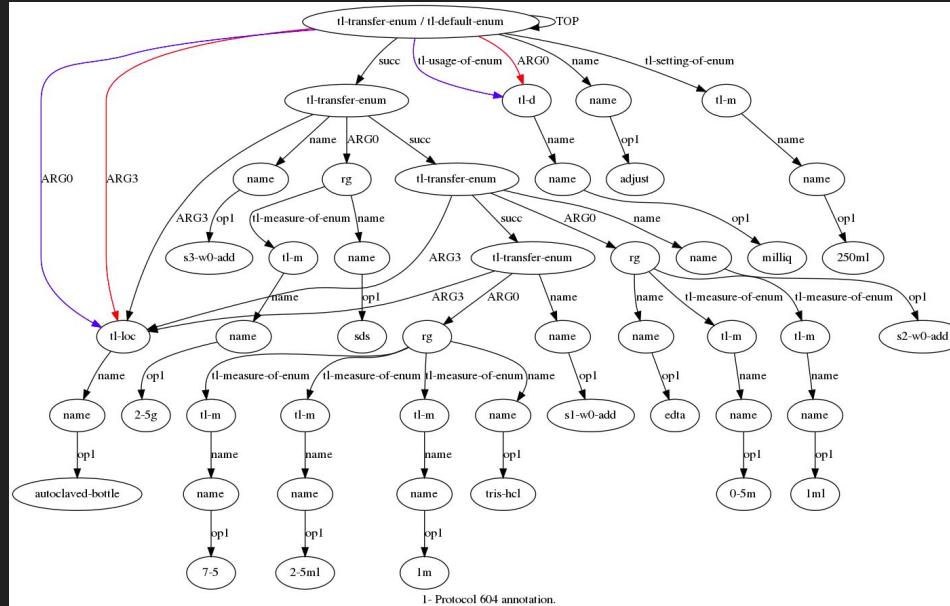
- > 3 annotators, enriched 279/622 (45%) WLP protocols to PEG format
- > Comparable with other procedural text datasets

Table 5: Statistics of our annotated corpus (X-WLP), compared with the ProPara corpus [Dalvi et al. [2018]], material science (MSPTC; [Mysore et al. [2019]]) and chemical synthesis procedures (CSP; [Vaucher et al. [2020]]). CSP is comprised of annotated sentences (document level information is not provided)

	X-WLP (ours)	MSPTC	CSP	ProPara
# words	54k	56k	45k	29k
# words / sent.	12.7	26	25.8	9
# sentences	4,262	2,113	1,764	3,300
# sentences / docs.	15.28	9	N/A	6.8
# docs.	279	230	N/A	488

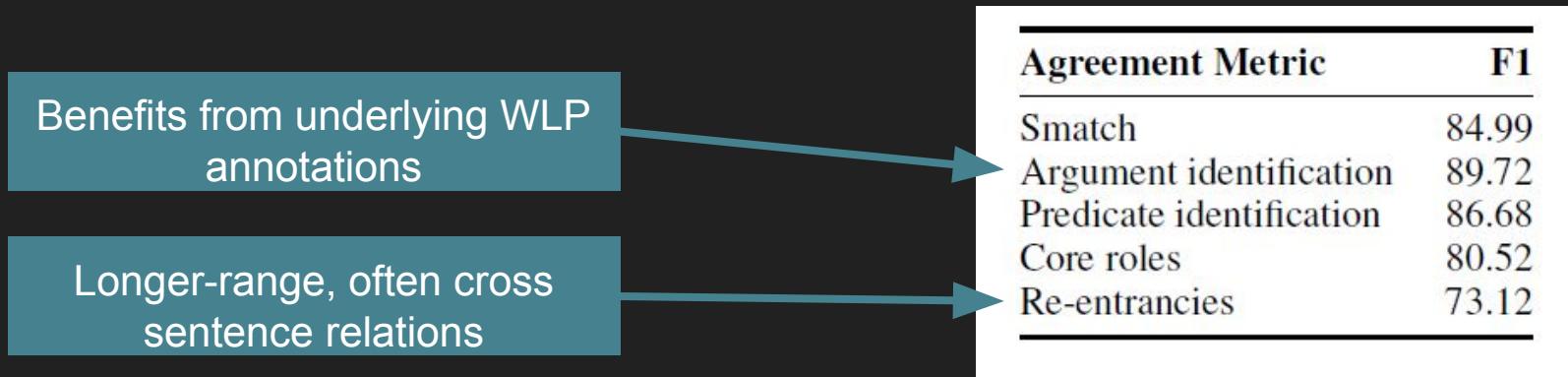
## Quantitative analysis: annotator agreement

- > Use Abstract Meaning Representation (AMR) format for established graph agreement metrics (Smatch, Cai & Knight, 2013)



## Quantitative analysis: annotator agreement

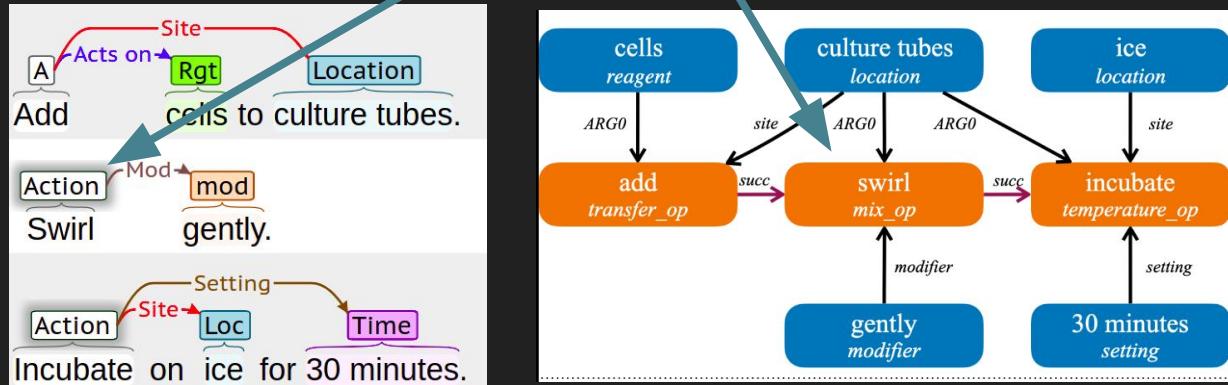
- > Use Abstract Meaning Representation (AMR) format for established graph agreement metrics (Smatch, Cai & Knight, 2013)
- > Mean 84.99 F1 Smatch comparable to AMR datasets (69 - 89 F1)



# Quantitative analysis: operation arguments

- > Simulator input validation prevents semantic underspecification, increases overall argument count per op.

Dataset	Avg. #args/op	#Ops. w/o core arg.	#Ops.	Pct.
WLP	1.87	3297	17485	18.9
X-WLP	3.01	0	3915	0.0



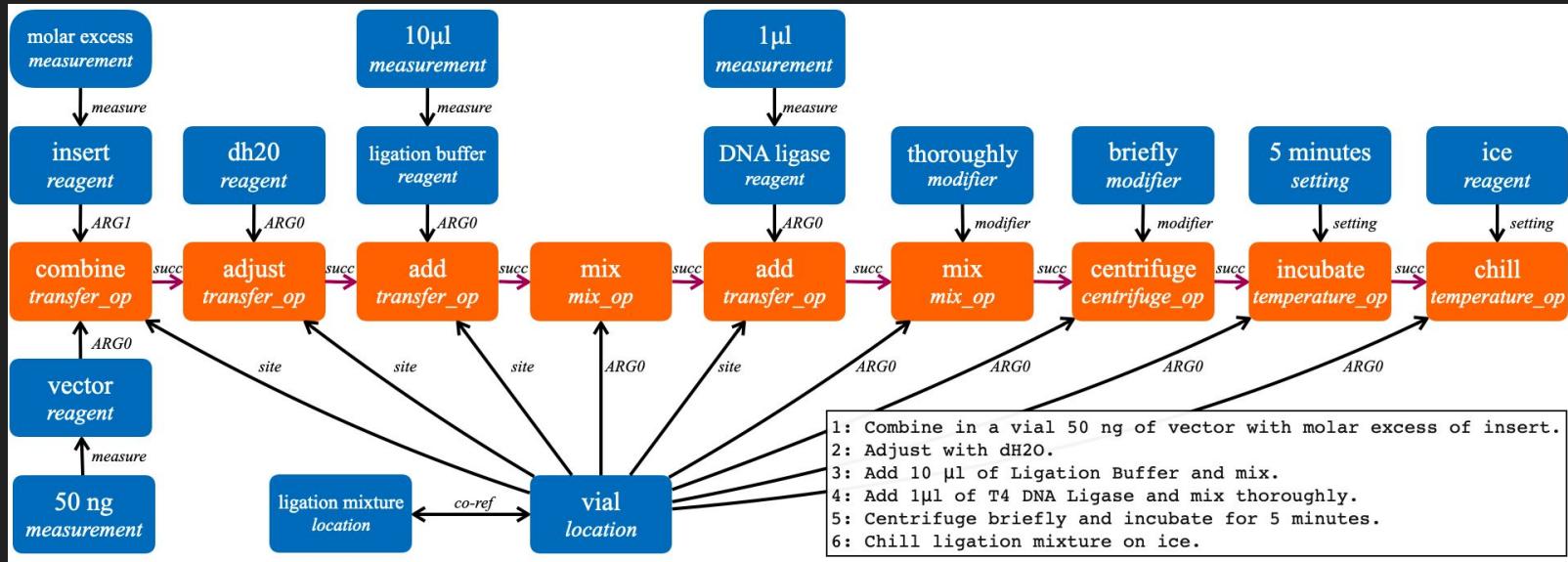
# Quantitative analysis: relation types

- > Significant proportion of arguments are re-entrancies (>30%)
- > Many cross-sentence co-reference relations (>90%) - provide process-level structure

Relation	# Intra.	# Inter.	Total	# Re-entrancy
Core				
• ARG0	2962	952	3914	1645
• ARG1	560	127	687	3
• ARG2	84	123	207	77
Total (core)	3606	1202	4808	1725
Non-Core				
• site	1306	325	1631	360
• setting	3499	2	3501	-
• usage	1114	24	1138	-
• co-ref	129	1575	1704	-
• located-at	199	72	271	-
• measure	2936	18	2954	-
• modifier	1861	2	1863	-
• part-of	72	65	137	-
Total (non-core)	11116	2083	13199	360

# Qualitative Analysis: complex co-reference

- > Many long-range metonymic co-references - what does “ligation mixture” refer to?



# Modelling

- > Tried two approaches:
  - Standard pipeline model based on SciBERT (Beltagy et. al, 2019)
  - Multi-task: jointly learn to predict entire PEG. Based on DyGIE++ (Wadden et. al, 2019)

# Modelling (1): Pipeline Approach

- > Train model for each sub-task, chain together to obtain full PEG

## 1 Mention identification

Add cells to culture tubes.  
Swirl gently.

## 2 Operation typing

transfer-op Add cells to culture tubes.  
mix-op Swirl gently.

## 3 Argument role labeling

site  
ARG0  
transfer-op Add cells to culture tubes.  
ARG0  
mix-op Swirl gently.  
modifier

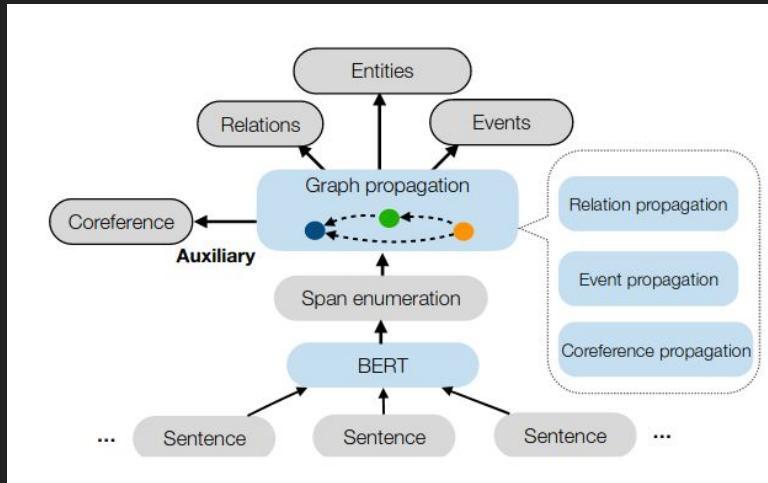
## 4 Temporal ordering

site  
ARG0  
transfer-op Add cells to culture tubes.  
ARG0  
mix-op Swirl gently.  
modifier

Legend: operation reagent location modifier

## Modelling (2): Multi-task Approach

- > Adapted DyGIE++ (Wadden et. al, 2019) for our protocols
  - Used sliding window as length exceeded SciBERT 512-token limit



DyGIE++ Framework (Wadden et. al, 2019)

# Results

## 1. Mention Identification

Data Split	System	$F_1$
original	Kulkarni et al. (2018)	78.0
	Wadden et al. (2019)	<b>79.7</b>
	PIPELINE	78.3

## 2. Fine-grained operation typing

System	P	R	$F_1$
MULTI-TASK	75.6	68.9	72.1
PIPELINE	69.2	78.4	73.6
• w/ gold mentions	78.6	81.0	<b>79.8</b>

# Results

3 + 4: Argument role labeling + temporal ordering (relation classification)

Task	MULTI-TASK	PIPELINE	# gold
Core			
• All roles	<b>59.2</b>	49.1	2839
• All roles (gold mentions)	-	70.8	2839
• ARG0	<b>62.0</b>	52.2	2313
• ARG1	<b>39.4</b>	28.9	412
• ARG2	<b>70.7</b>	57.4	114
Non-Core			
• All roles	<b>55.6</b>	44.6	4827
• All roles (gold mentions)	-	72.3	4827
• site	<b>60.5</b>	52.5	962
• setting	<b>77.4</b>	62.7	974
• usage	<b>35.0</b>	29.5	297
• co-ref	<b>41.2</b>	30.8	1014
• measure	<b>64.0</b>	52.6	804
• modifier	<b>50.0</b>	42.4	519
• located-at	<b>13.4</b>	10.5	179
• part-of	<b>8.5</b>	8.5	78
Temporal Ordering	<b>60.3</b>	49.0	1200
Temp. Ord. (gold mentions)	-	67.0	1200

Multi-task better on all relation-classification tasks, likely due to less cascading errors

Local (intra-sentence) relations easier to predict than cross sentence relations

# Results: intra vs inter sentence relations

- > For core-roles:

Split	MULTI-TASK	PIPELINE	# gold
Intra-sentence	<b>63.3</b>	55.6	2160
Inter-sentence	<b>42.1</b>	29.4	679

- > For co-reference (92% are inter-sentence):

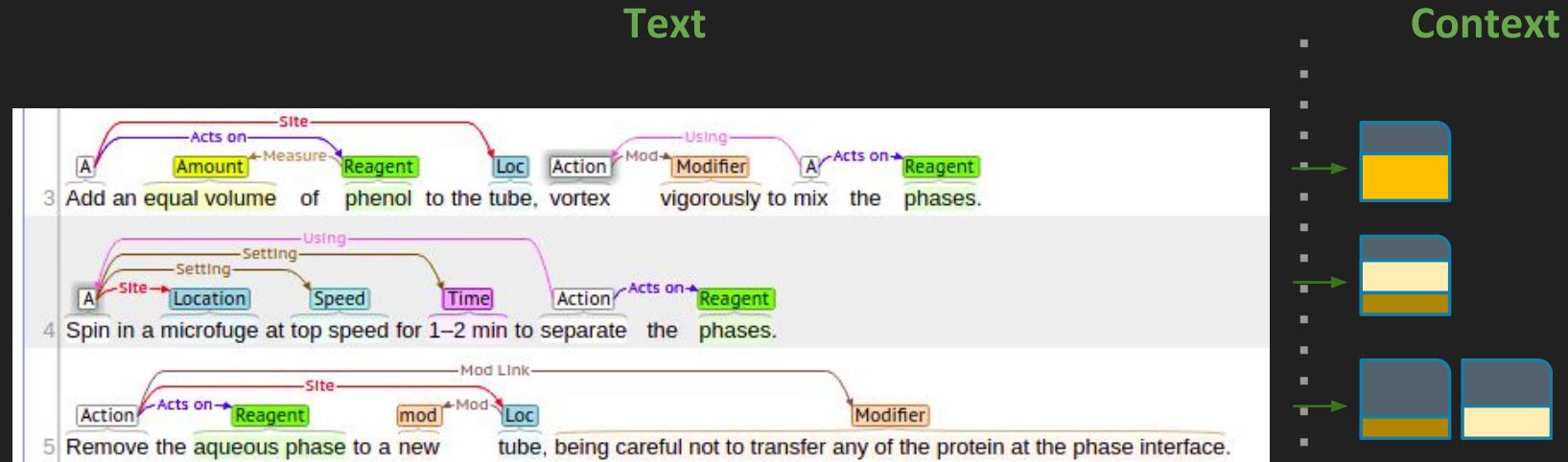
co-reference	<b>41.2</b>	30.8	1014
--------------	-------------	------	------

Cross-sentence relations ~ process-level  
information -> key challenge for modelling!

## Future work: modelling

- > Text-based game format allows alternate approach - predict instructions rather than predicting graph
- > Interactive semantic parsing setting - allows executing instructions and utilizing intermediate game state as context.

# Understanding protocols with context

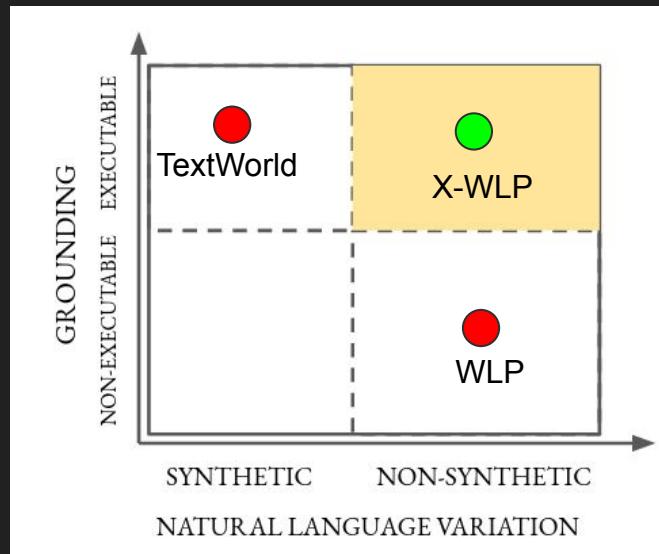


## Future work: improve interface

- > Reduce reliance on pre-existing annotations (e.g., allow creating new entities)
- > Ad hoc implementation, lots of improvements possible to facilitate more general applicability
  - Requires writing both Inform7 and Python, should require just one language...

# Towards grounded procedural text

- > Possible to obtain grounded annotations of long, complex real-world scientific texts- given the right framework!



# Concluding remarks

- > Simulator improves data quality through questification & validation
- > Modelling results highlight interesting process-level inference challenges
- > New take on annotation: simulation rather than labelling
  - Facilitates new training, modelling and evaluation methods
- > Data and simulator to be released with camera-ready!

THE END

Questions?