



Using an ontological representation of chemotherapy toxicities for guiding information extraction and integration from Electronics Health Records (EHRs)

Alice ROGIER, Adrien COULET, Bastien RANCE











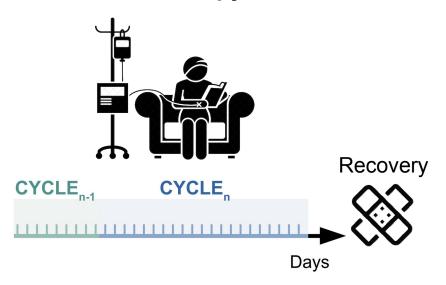




Context (1/2)

Adverse Drug Reaction (ADR) due to chemotherapy treatment

Chemotherapy treatment

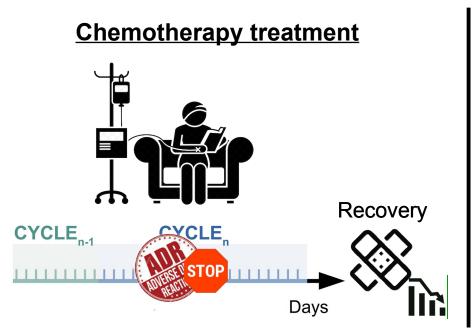




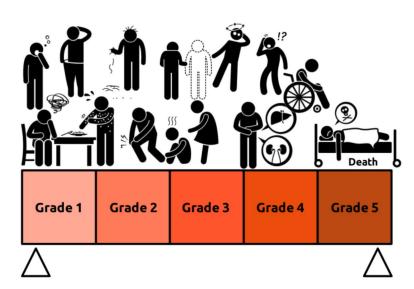


Context (1/2)

Adverse Drug Reaction (ADR) due to chemotherapy treatment



Adverse Drug Reaction (ADR)



Gastrointestinal disorders					
CTCAE Term	Grade 1	Grade 2	Grade 3	Grade 4	Grade 5
Esophageal stenosis	Asymptomatic; clinical or diagnostic observations only;	Symptomatic; altered GI function	Severely altered GI function; tube feeding or	Life-threatening consequences; urgent	Death
CTC AE+	intervention not indicated		hospitalization indicated; elective operative intervention indicated	operative intervention indicated	

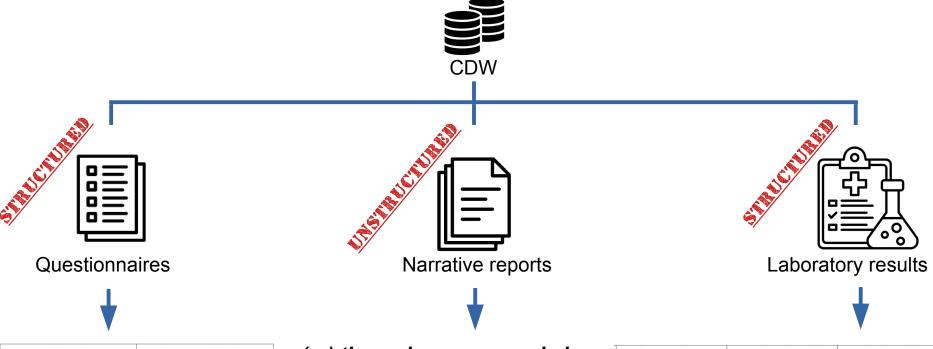




Context (2/2)

Toxicity sources in Clinical Data Warehouses (CDW)

Information about toxicities is available in CDW, but in heterogeneous forms



NAME_CHAR	TVAL_CHAR	
Asthenia	GRADE 1	

(...) the endoscopy revealed a peptic esophagitis of grade 2 with complications and (...)

NAME_CHAR	TVAL_CHAR	UNIT_CD
bilirubin	2	mg/dL





Objective

Integrating chemotherapy toxicities information in a common data model

Our contributions:



Creation of OntoTox, an **ontology** for chemotherapy toxicities guided by data



Toxicity extractions from different data sources



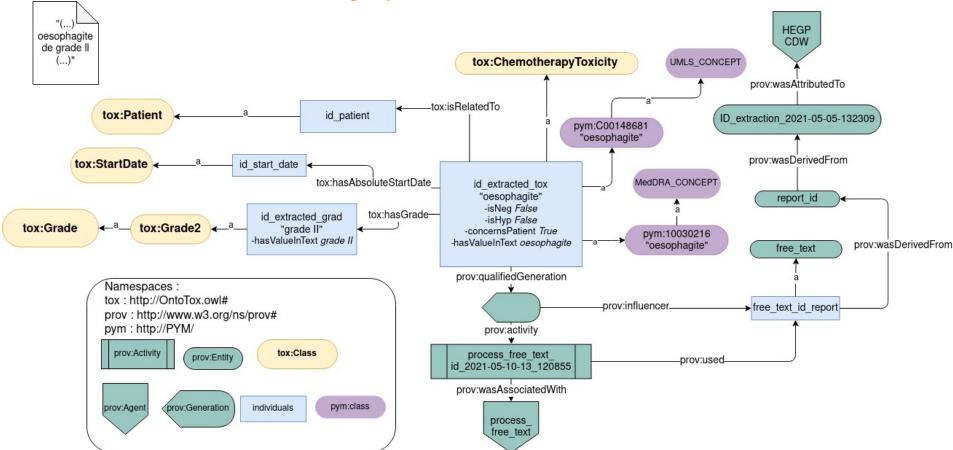
Demonstration of OntoTox interest with a clinical use case





OntoTox structure (1/3)

OntoTox classes: toxicity qualifications

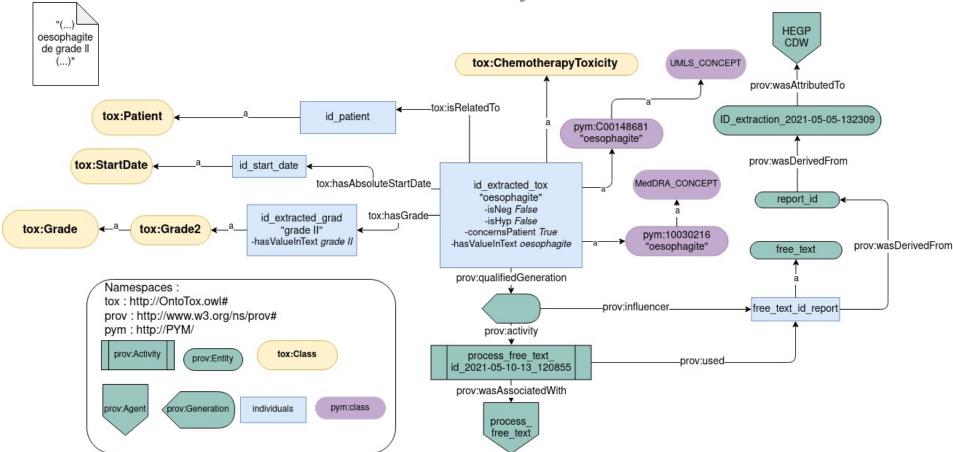






OntoTox structure (2/3)

MedDRA and UMLS classes: toxicity normalization

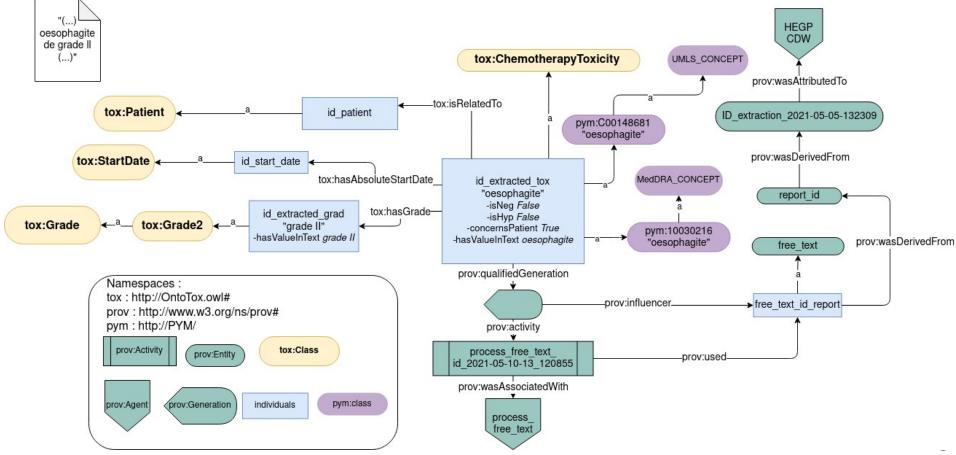






OntoTox structure (3/3)

PROV-O classes: toxicity provenance encoding







OntoTox implementation



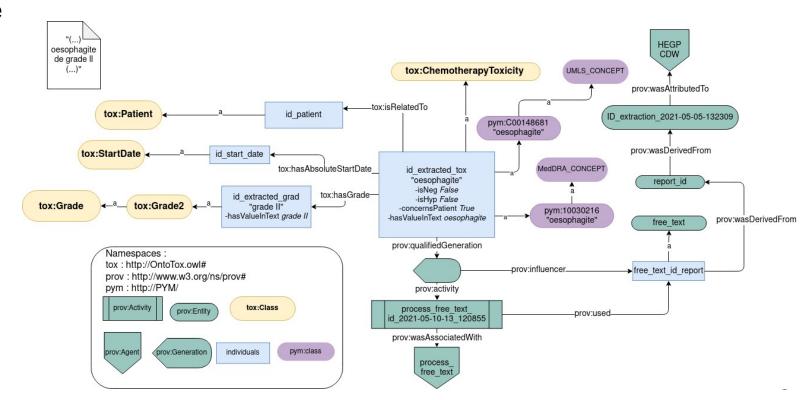
Data driven



Owlready, PyMedTermino



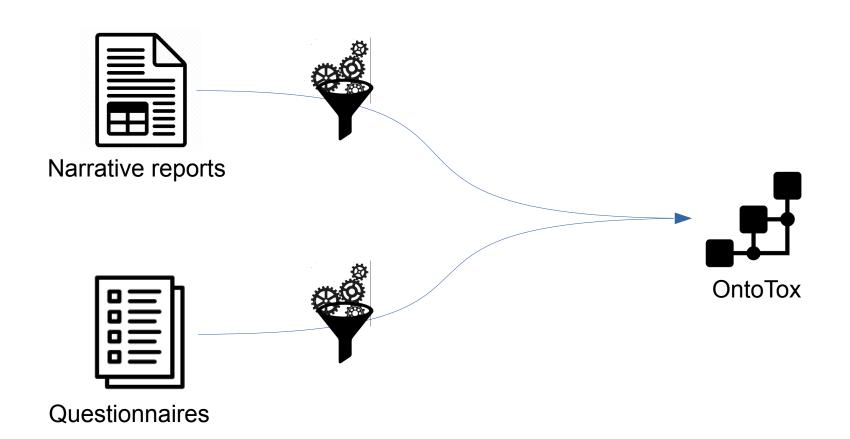
Protégé







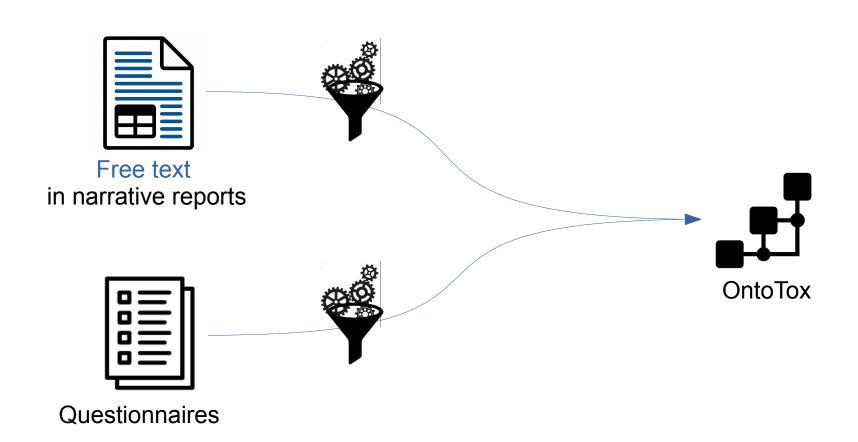
Extract and integrate chemotherapy toxicities in OntoTox







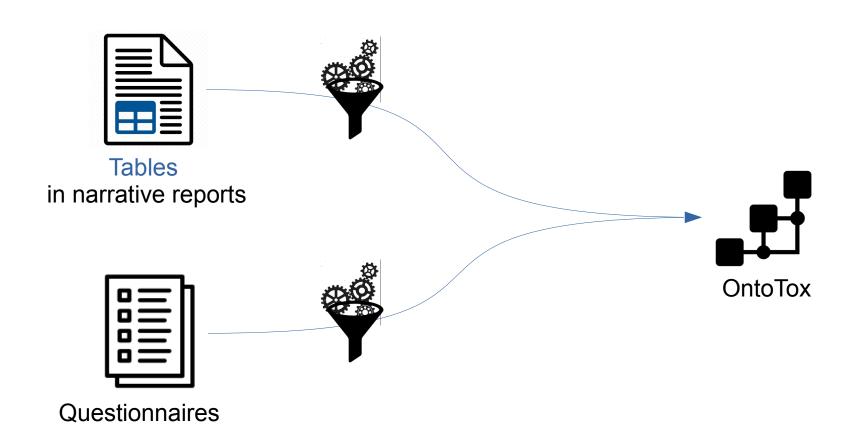
Extract and gather chemotherapy toxicities in OntoTox







Extract and gather chemotherapy toxicities in OntoTox



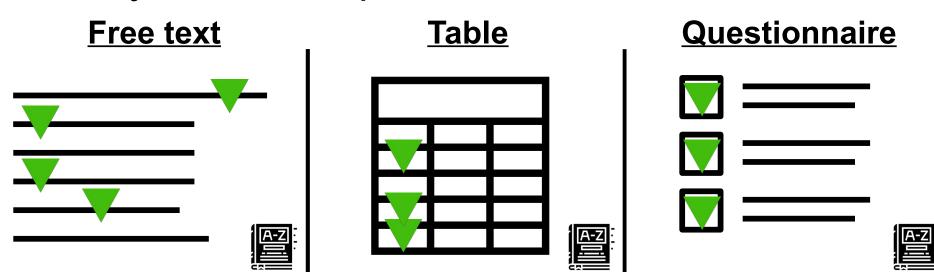




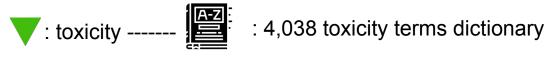
Free text	<u>Table</u>	Questionnaire	





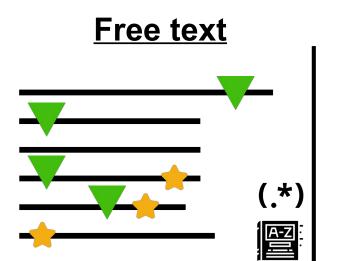


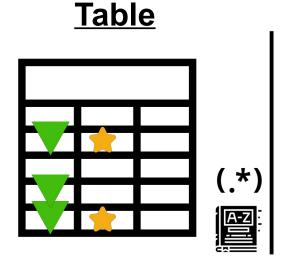
Entitiy recognition:

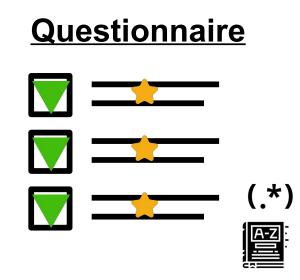




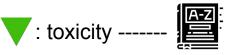








Entitiy recognition:



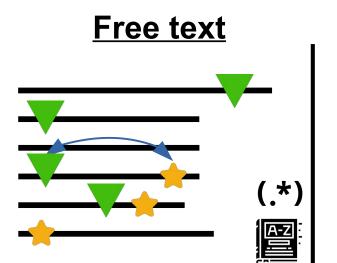
: 4,038 toxicity terms dictionary

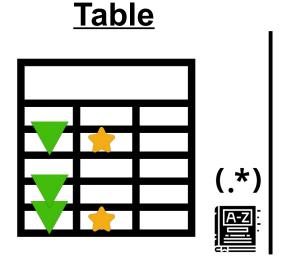


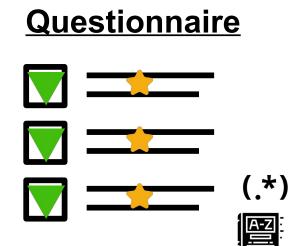
: regular expression



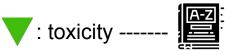








Entitiy recognition:



: 4,038 toxicity terms dictionary

: grade ----- (.*) : regular expression

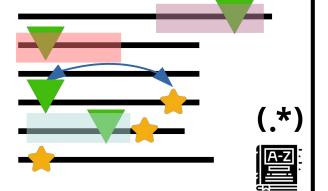


: Link between entities with dependency parsing

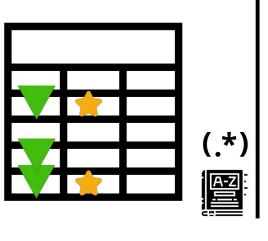




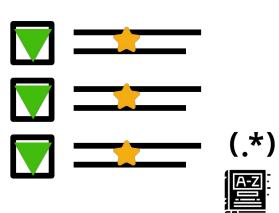
Free text



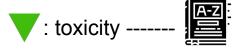
Table



Questionnaire



Entitiy recognition:





: 4,038 toxicity terms dictionary



🛖 : grade ----- (.*)



: regular expression

Context detection:

negation hypothesis

family

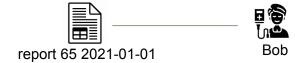


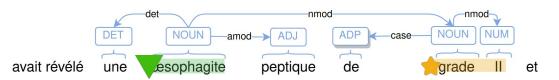
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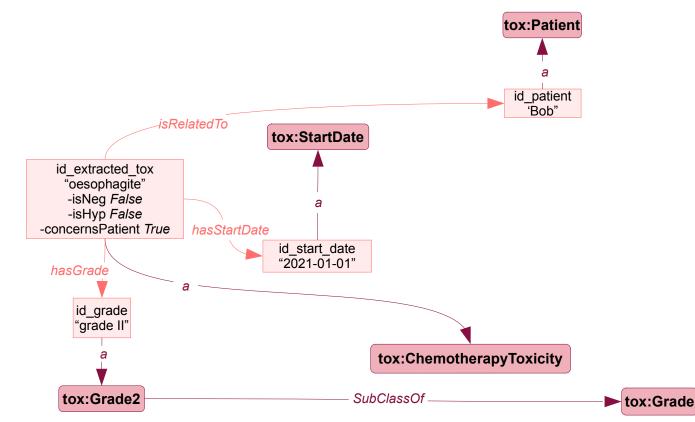




Example







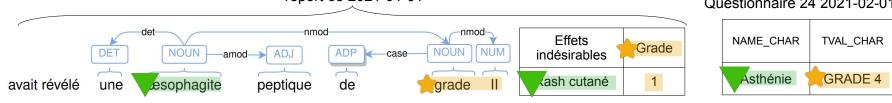
Example

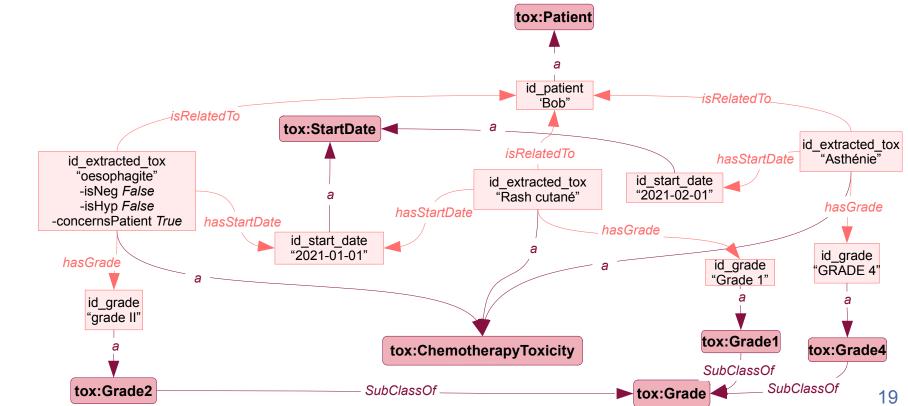
■ Toxicity extraction

Onto Tox instantiation

report 65 2021-01-01 Bob

Questionnaire 24 2021-02-01



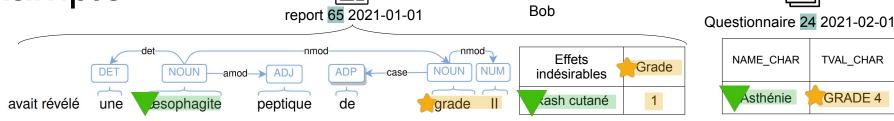


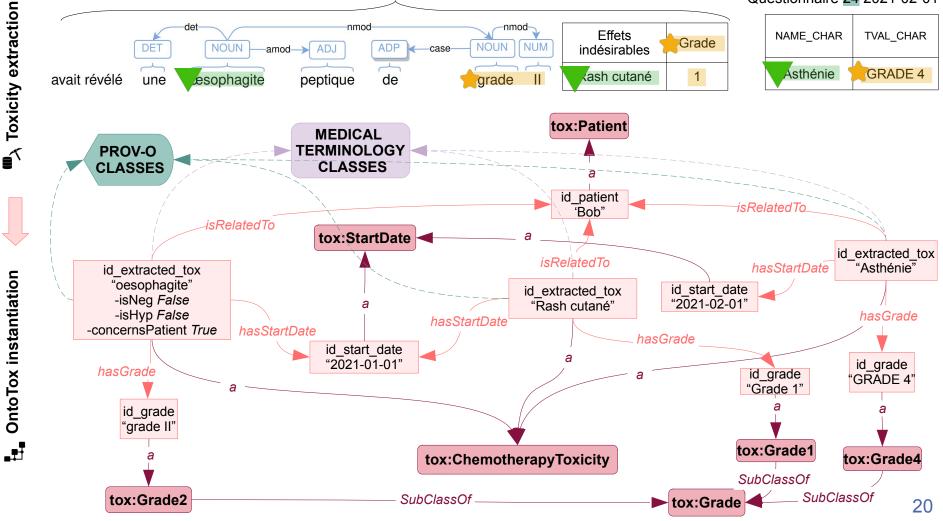




Example

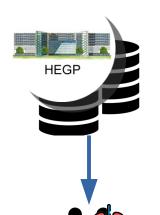
Onto Tox instantiation







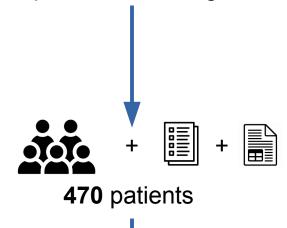
Use case





ICD=C34*

3,239 patients with lung cancer



≥1 questionnaire AND ≥ 1 report

Random sample

330 patients with **11,819** reports and **71,140** questionnaire items





Results (1/2): What is extracted?

OntoTox Classes			
ChemotherapyToxicity	54,420	2,366	53,510
Grade (ΣGrade <i>X</i>)	6,366	400	53,510
Grade1	2,100	87	9,981
Grade2	1,996	52	1,832
Grade3	817	23	191
Grade4	422	0	19
Grade5	2	1	0
Grade0	596	152	41,487
Grade <i>Null</i>	433	85	0





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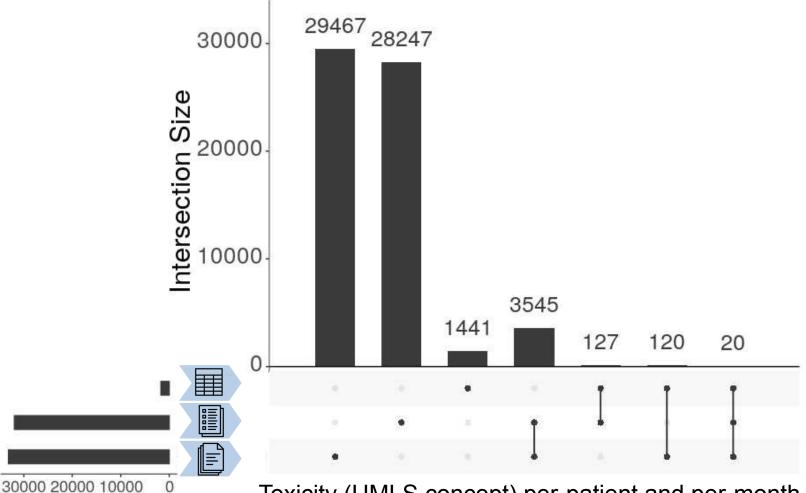
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Source



Results (2/2): How sources agree?



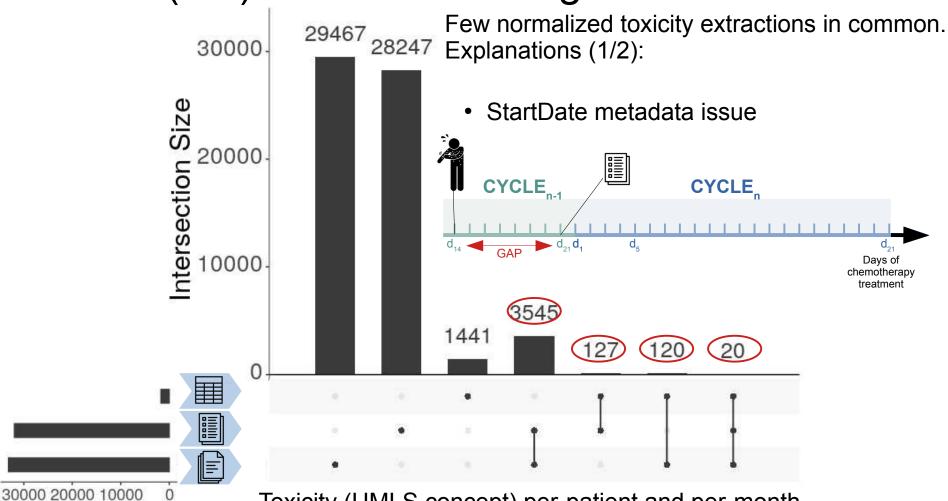
Toxicity (UMLS concept) per-patient and per-month intersection sets between the three sources



Source



Results (2/2): How sources agree?



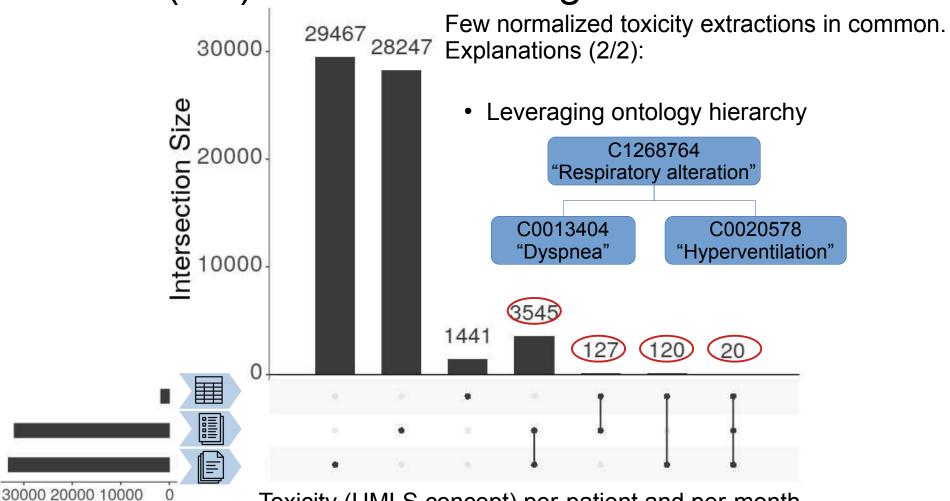
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Source



Results (2/2): How sources agree?



Toxicity (UMLS concept) per-patient and per-month intersection sets between the three sources





Discussion

OntoTox an ontology



- link to other knowledge models (PROV-O, MedDRA, UMLS)



- further use of reasoner

Room for improvement



- treatment representation



- time representation



勇 - leveraging ontology hierarchy for granularity



- Evaluate and improve extractions algorithms





Conclusion

Onto Tox...



very first ontology for chemotherapy toxicities



can guide the data integration from various sources



will be be enriched



will further serve as a brick for clinical decision support systems



Thank you!







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OntoTox GitHub:

https://github.com/TeamHeka/OntoTox



OntoTox BioPortal:

https://bioportal.bioontology.org/ontologies/ONTOTOX

Icons from Noun Project:

Fengquan Li Eucalyp Creative Stall Adrien Coquet Chanut is Indusries **Prettycons** H Alberto Gongora Smalllike visual world Pham Thi Dieu Linh icons alberto galindo Justin Blake Hrbon SA Family Ifki riantos Fajar **ProSymbols** Magicon Danil Polshin **Gregor Cresnar** Eynav Raphael angelina **Becris** 23 icons Hasanudin





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