# **OAEI-2022 Bio-ML Track: ML-Friendly Biomedical Datasets for Equivalence and Subsumption OM**

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## Introduction

### **Ontology Matching**

Example of matching T-Box named concepts through equivalence and subsumption relationships

#### FMA Axioms

VestibulocochlearNerve 🗆 CanialNerve VestibulocochlearNerve 🗆 🛛 branch.CochlearNerve VestibulocochlearNerve 🗌 🛛 branch.VestibularNerve CanialNerve 🗌 NeuralTreeOrgan





#### SNOMED Axioms

VestibulocochlearNerveStructure 🗆 CanialNerveStructure VestibulocochlearNerveStructure 🗌 PeripheralNerveOfHeadAndNeck CanialNerveStructure 🗌 NerveStructure

### Motivations: knowledge & data integration, quality assurance

Challenges for OM systems	Limitations
<ul> <li>Variety of naming scheme =&gt; synonyms; naming styles</li> <li>Ambiguity =&gt; similar naming but in different contexts</li> <li>Scalability =&gt; naïve traversal of OM takes O(n^2)</li> <li>Inconsistency =&gt; merging ontologies often lead to logical conflicts</li> </ul>	<ul> <li>Lack of high- standard ma</li> <li>Lack of a uni framework</li> <li>Often limited matching</li> <li>Lack of supp learning-bas</li> </ul>



## **Datasets and Settings**

Source	Task	Category	#Classes	#RefMaps (equiv)		#Classes	#RefMaps (subs)
Mondo	OMIM-ORDO	Disease	9,642-8838	3,721		9,642-8,735	103
Mondo	NCIT-DOID	Disease	6,835-8,848	4,684		6,835-5,113	3,339
UMLS	SNOMED-FMA	Body	24,182-64,726	7,256		24,182-59,567	5,506
UMLS	SNOMED-NCIT	Pharm	16,045-15,250	5,803	-	16,045-12,462	4,225
UMLS	SNOMED-NCIT	Neoplas	11,271-13,956	3,804		11,271-13,790	213
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#### Statistics for Equivalence Matching

- Matching: equivalence & subsumption
- Splitting: Unsupervised & semi-supervised
- Evaluation: global matching & local ranking

#### s of Existing OM Data

-quality gold appings ified evaluation

d to equivalence

ort for **machine** sed systems



## **Overall Workflow**

Statistics for Subsumption Matching

### **Equivalence Matching**

- (and -DL)
- LSMatcher
- scores of all tasks

#### **Subsumption Matching**

- ML-based systems including Word2Vec, OWL2Vec\*, BERTSubs
- BERTSubs performs the best on 2 out of 5 subsumption tasks, while OWL2Vec\* performs the best on the remaining 3
- No participation of traditional systems

- Still too few participants using ML methods
- Only 3 participants on subsumption matching which is more challenging
- Some participants only submit the results
- How to encourage both reproducibility and participation enthusiasm?
- is required



## 

## Samsung Research

## **Participants & Results**

ML-based systems including BERTMap (and -Lite), AMD, Matcha

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Traditional systems including LogMap (and -Lite), ATMatcher,

• ML systems generally perform better with Match-DL attaining best F1 on 4 out of 5 semi-supervised tasks, BERTMap (and lite) attains best F1 on 4 out of 5 unsupervised tasks, and best ranking

Full results: https://www.cs.ox.ac.uk/isg/projects/ConCur/oaei/2022/#results

## **Conclusion and Discussion**

A systematic benchmarking study on ML-based OM systems