# **Generic Entity Resolution Models**

**Link** to the paper:

https://github.com/jiaweitang0202/generic.entity.resolution/blob/main/ger.pdf

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### **The Entity Resolution Problem**

Given two entities **a** and **b**, decide if (**a**, **b**) match or not? Answer: 1 (match)



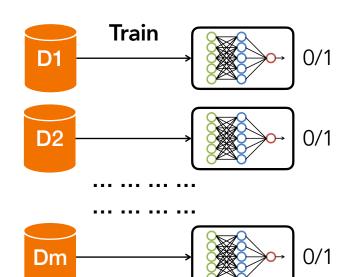
Company	Address	City
P Sherman Orthodontics	32 Wallaby Way	Sydney, NSW



# **Specific Models vs. Generic Solutions**

## **Specific Solutions**

- traditional wisdom -

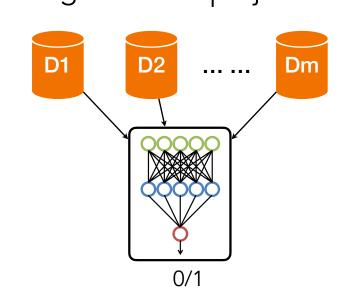


#### Limitations

- 1. Need a lot of train data : for each dataset
- 2. Lack of generalizability
- 3. Large sizes

### **Generic Solutions**

- goal of this project -

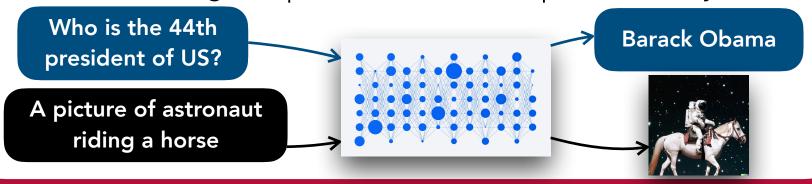


#### **Opportunities**

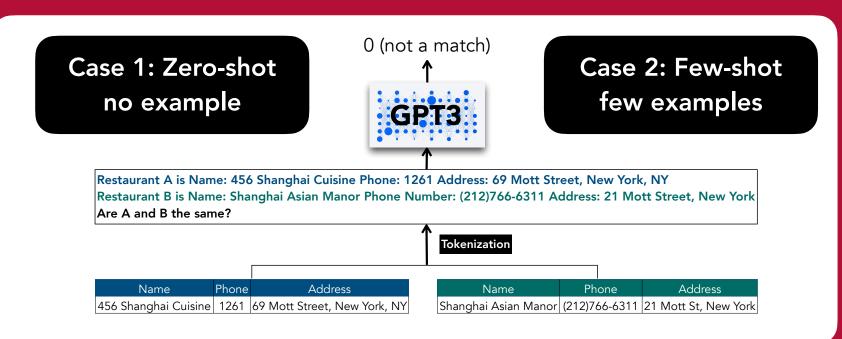
- 1. Foundation models
- 2. A trained generic model

#### **Foundation Models**

Foundation models are giant artificial intelligence models trained on a large corpus of data and can perform many tasks



# **Foundation Models for Entity Resolution**

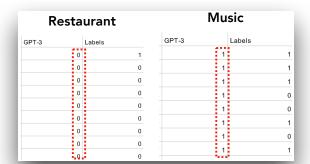


# **Experiments with Foundation Models**

#### **Zero-shot results**

Dataset	Precision	Recall	F-messure		
Restaurant	0.991	0.919	0.954		
Bike	1	0.1	0.182		
Movie	0.714	0.368	0.486		
Book	0.632	0.598	0.615		

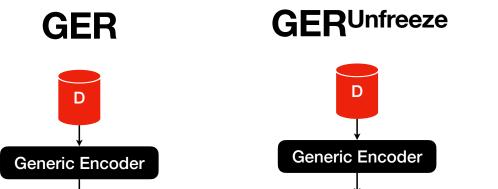
## **Few-shot results**



- 1. Under zero-shot, GPT3 works, but underperforms specific solutions
- 2. Few-shot gives very biases results (either all 0's or all 1's)
- 3. **Conclusion**: Zero-shot should be used on GPT3 for entity resolution

## **A Trained Generic Model**

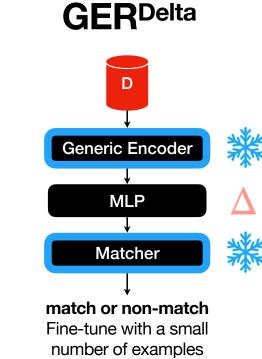
Designed three solutions for building generic models



match or non-match match or non-match (zero-shot) Fine-tune with a smal number of examples

Catastrophic forgetting

Matcher



# **Experiments with Generic Models**

	Specific Model				GPT-3			GER		
Dataset	Р	R	F1	Р	R	F1	Р	R	F1	
Restaurant	0.941	0.941	0.941	0.991	0.919	0.954	0.978	0.936	0.956	
Bike	0.773	0.548	0.642	2 1	0.1	0.182	0.405	0.81	0.54	
Movie	0.978	0.957	0.968	0.714	0.368	0.486	0.873	0.984	0.925	
Book	1	1	1	0.632	0.598	0.615	0.837	1	0.911	
	GER <sup>Unfreeze</sup>				GER <sup>Delta</sup>					
Dataset	Р	R		F1	Р		R		F1	
Restaurant	0.979	0.95	57	0.968	0.93	9	0.979	0.	958	
Bike	0.554	0.85	57	0.673	0.56	6	0.881	0.	685	
Movie	1	0.98	34	0.992	1		0.984	0.	992	
Book	0.973	1		0.986	0.93	35	1	0.	966	

- 1. Both GER<sup>Unfreeze</sup> and GER<sup>Delta</sup> can be adapted to a new task with a few train examples
- 2. If one still wants the entity resolution model to perform well on previously trained ER datasets, then GERDelta should be used