SEMINAR

# AI AND DUPLICATE DETECTION TO LEVERAGE EXTERNAL DATA SOURCE

April 21st

# ABOUT MYSELF

**DAVID BEAUCHEMIN**
Ph. D. candidate in ML
Laval University

- B. Sc. in actuarial science
- M. Sc. in computer science, ML and NLP
- 5 years in academic ML and NLP researc project
- +6 years of various applied business projects
- Founder and creator of OpenLayer ↗* a bilingual AI podcast
- Founder of .Layer ↗* a data science non-profit organisation

# MENU

1. What is our problem ?
2. How can we develop a solution for that ?
3. How can we compute the similarity between two entities ?
4. Why develop our own solutions ?

## What is our problem?

# WHAT IS OUR PROBLEM?

$

Data is not cheap

# WHAT IS OUR PROBLEM ?

A lot of open data now (data.gouv ↗*)

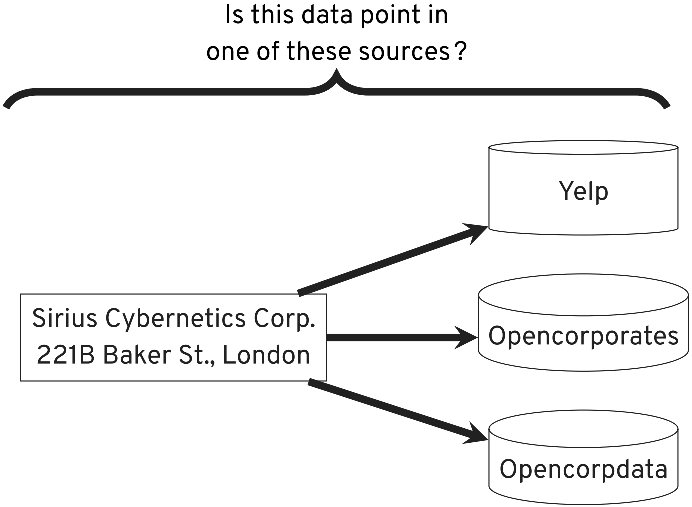
# WHAT IS OUR PROBLEM?

Mapping between datasets

## AN EXAMPLE

Only using the name and the address of a business client is it possible to match these with external sources to leverage their content?

## AN EXAMPLE



Is this data point in
one of these sources?

Sirius Cybernetics Corp.
221B Baker St., London

Yelp

Opencorporates

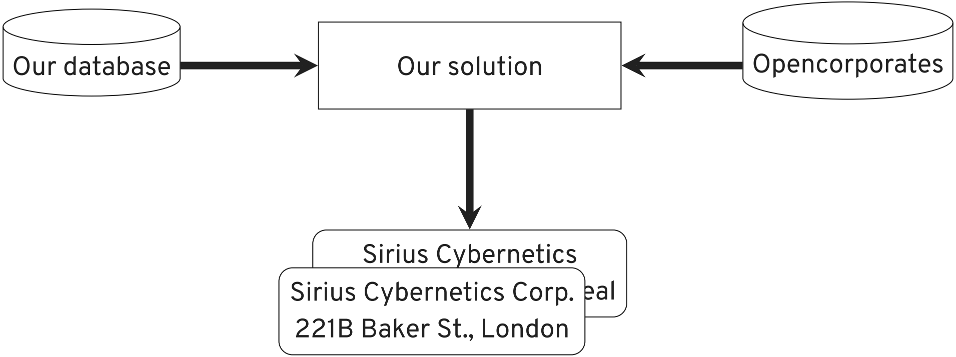
Opencorpdata

## AN EXAMPLE

How can we match our information with external data sources if we do not control it and our information is not unique?

# How can we develop a solution for that?

## WHAT OUR SOLUTION NEEDS TO DO ?



Our database

Our solution

Opencorporates

Sirius Cybernetics

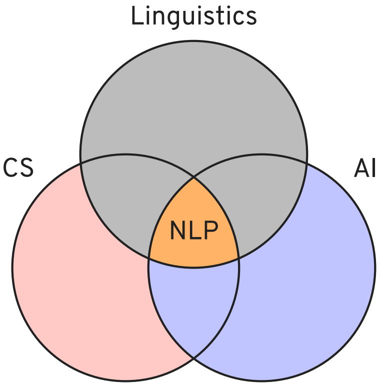
eal

Sirius Cybernetics Corp.
221B Baker St., London

## WHAT DO WE NEED TO ACHIEVE THAT?

- Natural language processing (NLP)
- A duplicate detection mechanism

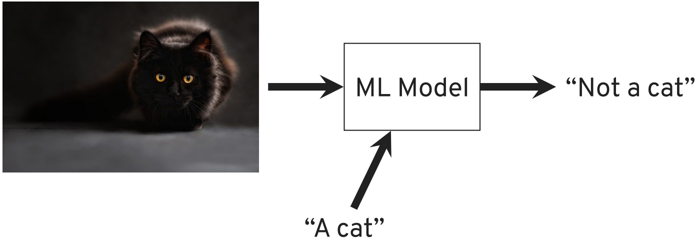
# WHAT IS NLP?



## WHAT IS AI ?

A cat or not ?

## WHAT IS AI?

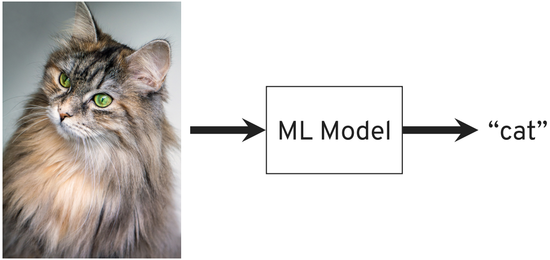


ML Model

“Not a cat”

“A cat”

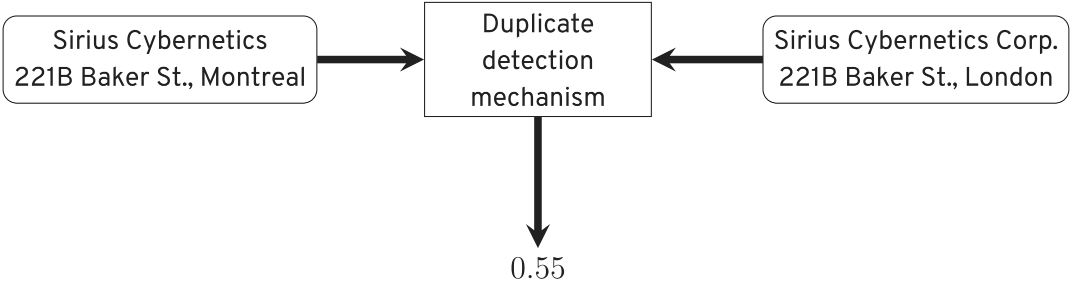
# WHAT IS AI?



ML Model

“cat”

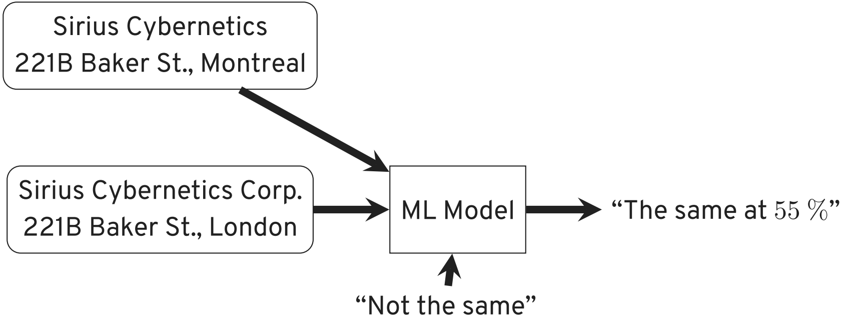
# DUPLICATE DETECTION MECHANISM



# DUPLICATE DETECTION MECHANISM

- Rules-based
- Probabilistic
- ML

# ML DUPLICATE DETECTION MECHANISM



Sirius Cybernetics
221B Baker St., Montreal

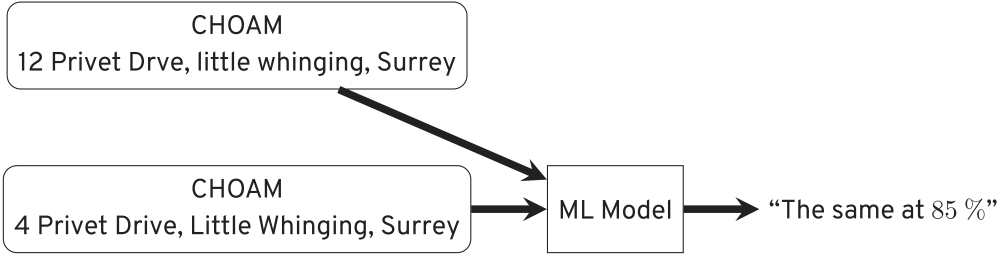
Sirius Cybernetics Corp.
221B Baker St., London

ML Model

“The same at $55\ \%$”

“Not the same”

# ML DUPLICATE DETECTION MECHANISM



CHOAM
12 Privet Drve, little whinging, Surrey

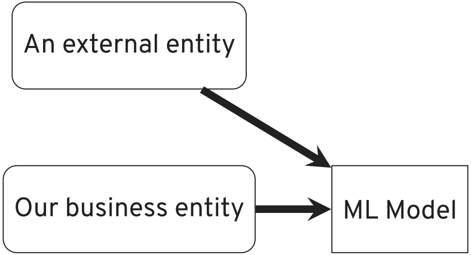
CHOAM
4 Privet Drive, Little Whinging, Surrey

ML Model

“The same at $85\,\%$”

## How can we compute the similarity between two entities?

## SIMILARITY ALGORITHM

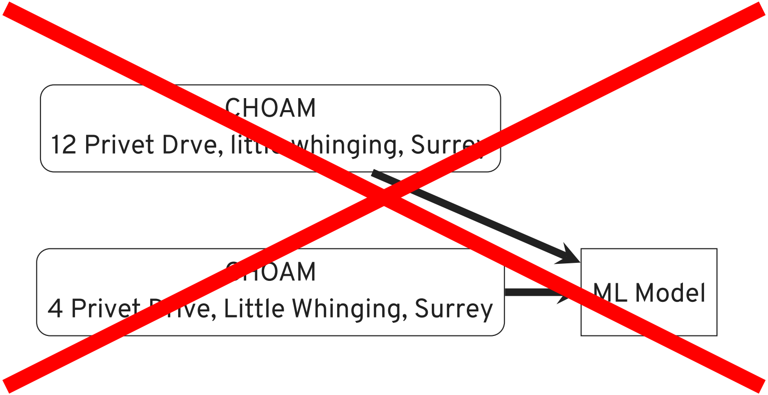


An external entity

Our business entity

ML Model

# SIMILARITY ALGORITHM



CHOAM

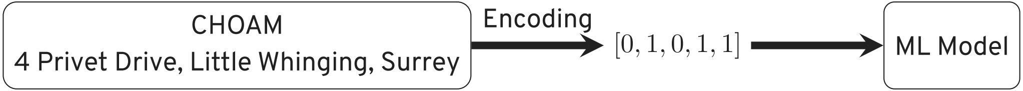
12 Privet Drve, little whinging, Surrey

CHOAM

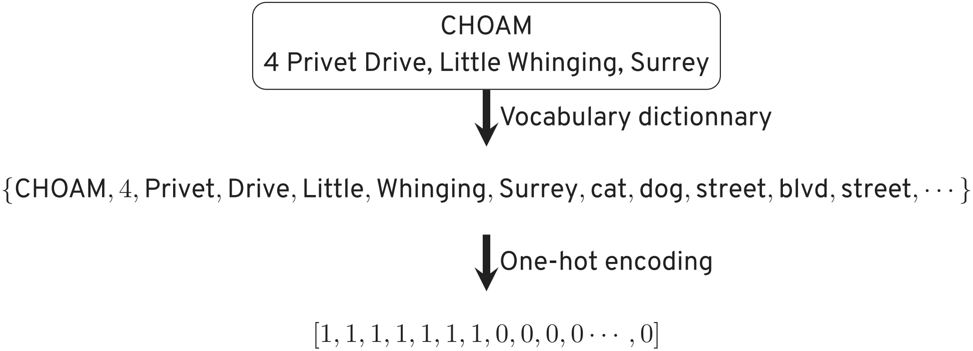
4 Privet Drive, Little Whinging, Surrey

ML Model

## NLP ML ALGORITHM



# ONE-HOT ENCODING



CHOAM
4 Privet Drive, Little Whinging, Surrey

Vocabulary dictionnary

$\{\text{CHOAM}, 4, \text{Privet}, \text{Drive}, \text{Little}, \text{Whinging}, \text{Surrey}, \text{cat}, \text{dog}, \text{street}, \text{blvd}, \text{street}, \cdots\}$

One-hot encoding

$[1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0 \cdots, 0]$

# ONE-HOT ENCODING

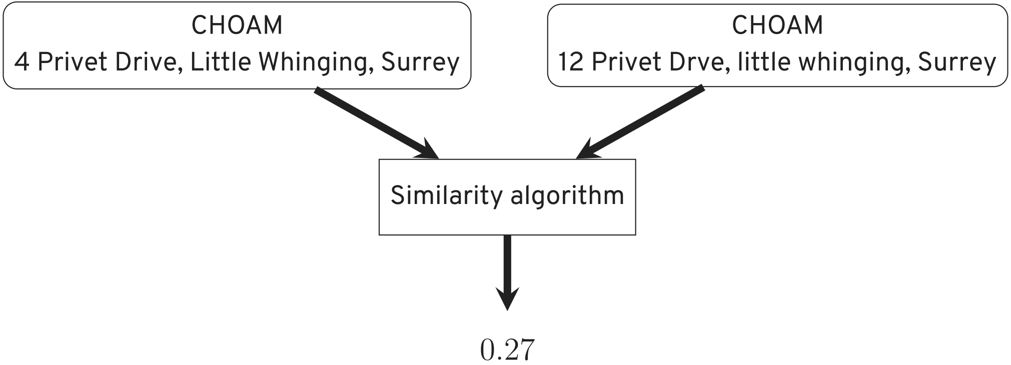
Advantages

- Easy to implement
- Not complex
- Easy to encode

Disadvantages

- Sparse
- Out-of-vocabulary

## SIMILARITY ALGORITHM



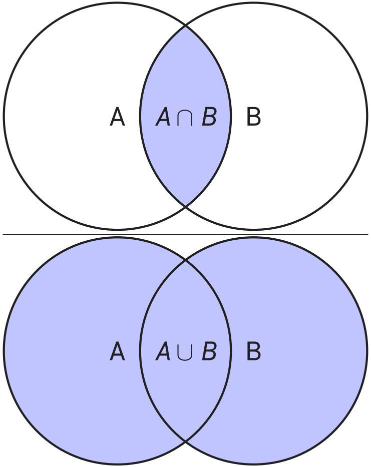
CHOAM
4 Privet Drive, Little Whinging, Surrey

CHOAM
12 Privet Drve, little whinging, Surrey

Similarity algorithm

$0.27$

## JACCARD



# JACCARD

$$\frac{\{\text{CHOAM}, \text{Privet}, \text{Surrey}\}}{\{\text{CHOAM}, 4, 12, \text{Privet}, \text{Drive}, \text{Drve}, \text{Little}, \text{little}, \text{Whinging}, \text{whinging}, \text{Surrey}\}} = \frac{3}{11} = 0.2727$$

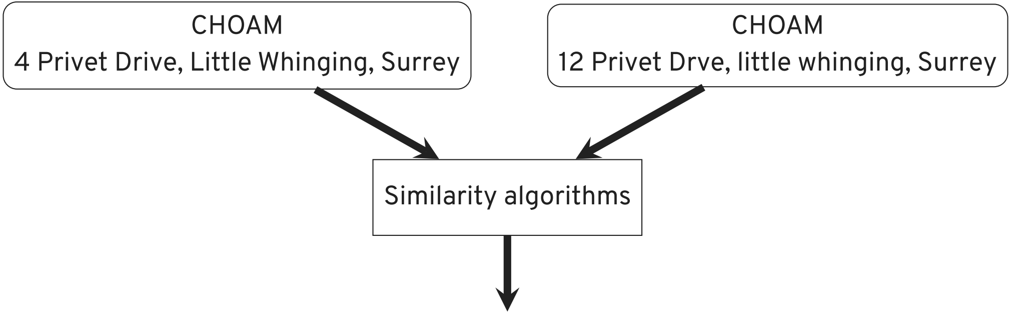
# JACCARD

$$\frac{\{\text{choam}, \text{privet}, \text{little}, \text{whinging}, \text{surrey}\}}{\{\text{choam}, 4, 12, \text{privet}, \text{drive}, \text{drve}, \text{little}, \text{whinging}, \text{surrey}\}} = \frac{5}{9} = 0.5556$$

## SIMILARITY ALGORITHM

- Jaro
- Jaro-Winkler
- Levenshtein
- Longest common subsequence
- Cosinus
- MASI
- Monge Elkan
- Overlap

## SIMILARITY ALGORITHM



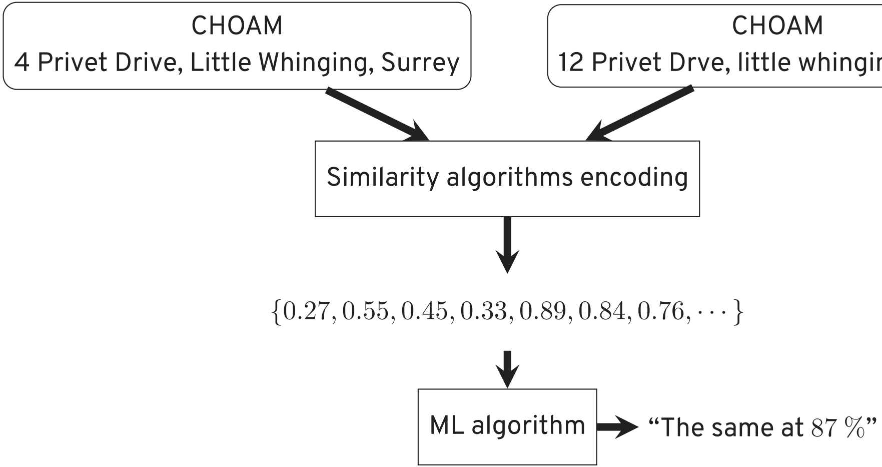
CHOAM
4 Privet Drive, Little Whinging, Surrey

CHOAM
12 Privet Drve, little whinging, Surrey

Similarity algorithms

$$\{0.27, 0.55, 0.45, 0.33, 0.89, 0.84, 0.76\}$$

# FINAL APPROACH



CHOAM
4 Privet Drive, Little Whinging, Surrey

CHOAM
12 Privet Drve, little whinging, Surrey

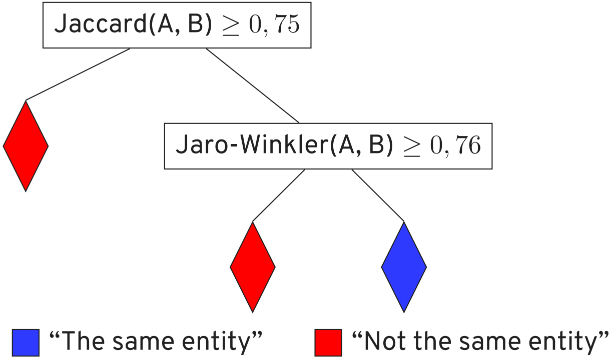
Similarity algorithms encoding

$$\{0.27, 0.55, 0.45, 0.33, 0.89, 0.84, 0.76, \cdots\}$$

ML algorithm

“The same at $87\ \%$”

# ML ALGORITHM



Jaccard(A, B) $\geq 0,75$

Jaro-Winkler(A, B) $\geq 0,76$

🟦 “The same entity” 🟥 “Not the same entity”

# NAME-ADDRESS INFORMATION VECTOR GENERATOR

**Example of an information vector**

| StoS | Levenshtein | Jaro-Winkler | LCSP | Jaccard | Cosinus | - |
|---|---|---|---|---|---|---|
| 0.00 | 0.15 | 0.25 | 0.35 | 0.15 | 0.15 | - |
| StoS | Levenshtein | Jaro | LCSP | Jaccard | Cosinus | CSS |
| 0.00 | 0.16 | 0.55 | 0.15 | 0.45 | 0.37 | 0.48 |

# RESULTS

|  | Logistic Regression | Random Forest | Multilayer perceptron | Jaccard |
|---|---|---|---|---|
| Recall (%) | 66.67 | 73.54 | **79.73** | 72.51 |
| Precision | **89.77** | 81.06 | 87.55 | 81.78 |

Detection of Duplicates Among Non-structured Data From Different Data Sources*

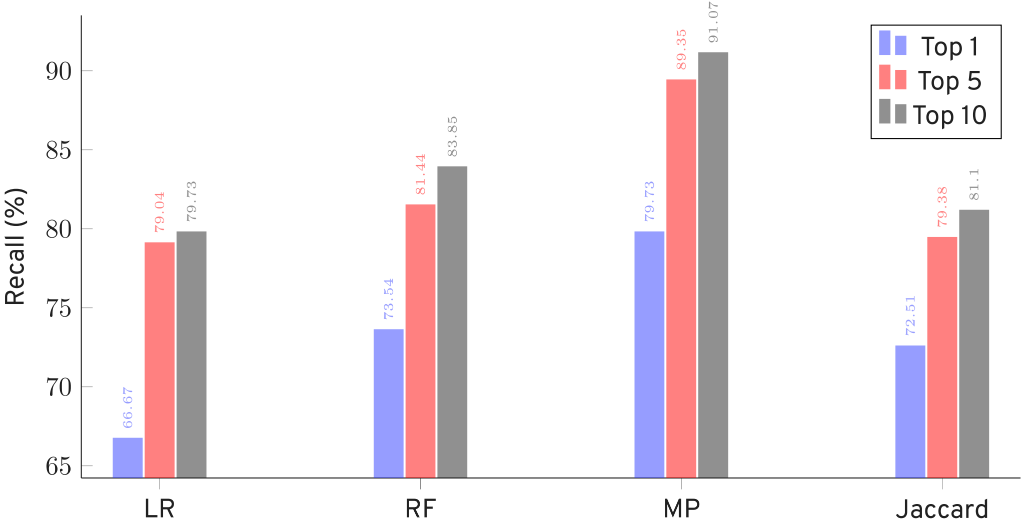
# INFERENCE TIMES

| (second) | Logistic Regression | Random Forest | Multilayer Perceptron | Jaccard |
|---|---|---|---|---|
| Time | 1,32 | 1,74 | 1,34 | 0,25 |

## IMPROVING THE RESULTS - *N* MOST SIMILAR

We consider a matching is good when the pair *(Our database entity, external data source entity)* is included in the *N* most similar rather than the top-1.

## IMPROVING THE RESULTS - *N* MOST SIMILAR



# Why develop our own solutions?

# WHY DEVELOP OUR OWN SOLUTIONS?

There is commercial solutions out there, why not buying it?

# WHY DEVELOP OUR OWN SOLUTIONS?

- Help empower your teams on important NLP steps,
- It is a straightforward classification problem.

## CONCLUSION

- NLP can help you bring value to your business.
- I have presented a solution that one can develop to detect duplicates using NLP and ML.
- Without deep learning, you can achieve interesting results in duplicate detection with external data sources.

SEMINAR

# THANK YOU FOR LISTENING!