

# Catching the big corporates – record linkage algorithm for company names

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## Context: What is in my contract?

6

Reinsurance?



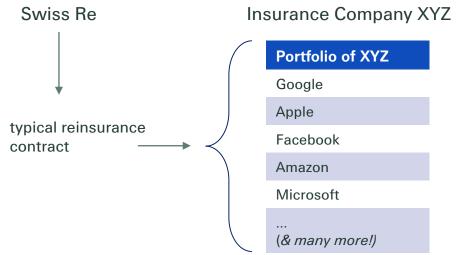
"insurance for insurers":



Reinsurance contract?



insures/covers an insurance *portfolio*:



# The tough job of identifying companies

**Status quo** "What companies are in my contract?"

- 1. We need a 'reference' company repository
- 2. We need to map it to your portfolio

#### Problem "Real-life data is messy & complex"

Google Alphabet • BMW Bayerische Motorwerke AG

#### **Our Solution**

## "CorpFinder"

#### R package for record linkage of company names

 Using similarity-based string matching; taking into account corporate ownership tree; explicitly accounting for legal entity suffixes; using ad-hoc deduplication approaches...

# Why to search for large corporates?

Large Corporate Risks (LCRs) present special characteristics for a (re)insurer:

#### – Deep pockets:

- Reputation leads to legal costs.
- Reparation costs are large.



- Complex subsidiary structure.
- Accumulation of risk exposure.







# Entity (record) linkage

#### Deterministic record linkage

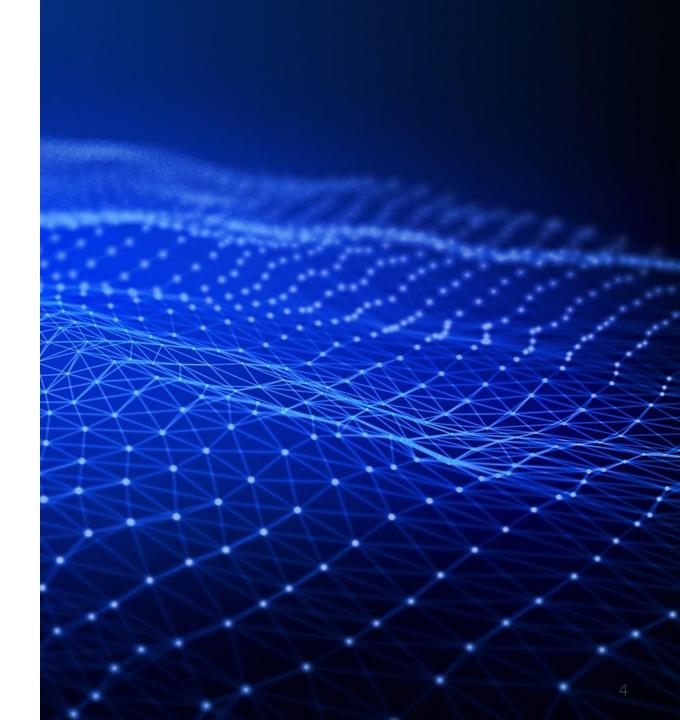
## Probabilistic record linkage

- String distance measures
  - => Better control/interpretability than ML
  - => Efficient when only one dimension available

## Machine Learning methods

- Regression
- Naïve Bayes method
- GNN





## Our modular solution

Component I
Company name
normalization

Component II

Matching to reference list

Component III
Disambiguation

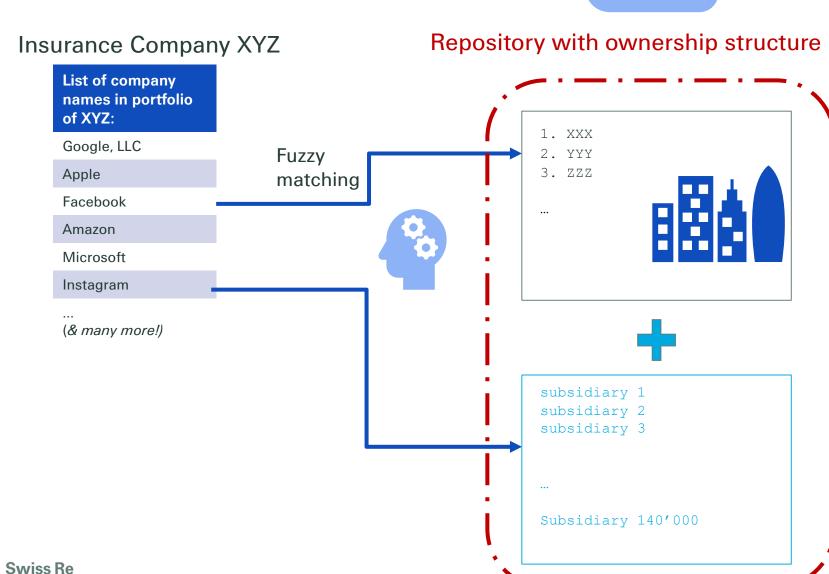
## Component I: Name normalization

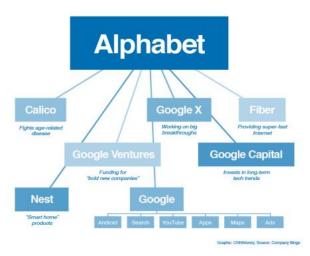
- Specificity of company names: often contain legal suffixes or prefixes, and in no consistent way:
  - *Apple Inc.* vs Apple vs. *Apple Incorporated* vs. *Apple Inc* describe the same entity.
  - Specific to languages, countries and legal structures: *pjsc* [russian], *oyj* [finish], *sa/nv* [belgium], etc...
- Hence: legal suffixes are isolated away from company names, based on an ad-hoc 'legal dictionary' (but they are kept and stored for use in *Component III*)
- Various additional normalization steps (stopwords removal, accent/special characters standardization, etc.)
- Considering 'aliases': e.g. BMW vs Bayerisches motorwerk



# Component II: Fuzzy-matching







## In practice

- Take 'normalized names' as input on both sides and compute pairwise distance
- Pick best score (as given by metric) as 'match', using a threshold

# Component II: Fuzzy-matching

## Which metric do we pick?

- Levenshtein
- Jaro-Winkler
- Jaccard (or tokenbased)

How to set a threshold?

 Fine-tune using a testset to keep sensitivity/recall balanced How to improve performance?

- Parallelize
- Cache
- Reduce search space

## Component III: Disambiguation

- Problem: How to handle matches with equally good score?
  - E.g. "Coca-Cola" vs. "Coca-Cola US" and "Coca-Cola UK"
  - "Freedom" vs. "Freedom Corp." and "Freedom SAS"

- ...

#### Our solution:

- 'Forbidden' associations: e.g. Apple Ltd cannot match Apple Inc
- **Different countries**: e.g. *Apple SAS* cannot match with *Apple Inc*.
- Matches on same tree: If matches belong to the same ownership tree, the entry is matched to the root of the
  entries



## Details of the package

- Not on GitHub but planning to make it available by 2021
- Access to our package
  - Shiny application for internal users: file upload for fuzzy matching
  - Package deployed on Cran:
    - Exported functions set up using one list of configuration
    - Fuzzy matching with a pre-defined or any user-defined list



## Outlook

- Open-source package on GitHub
- Inclusion of multiple dimensions
- Probabilistic record linkage as a reference for ML techniques
- User-trained ML algorithm

