The German Production Pipeline

Frankfurt - Data Model, Re-Structuring & Linking

Dennis Gram, Pantelis Karapanagiotis, Marius Liebald

Groningen Workshop

May 4, 2023

The Data Model

Dennis Gram

Starting Point

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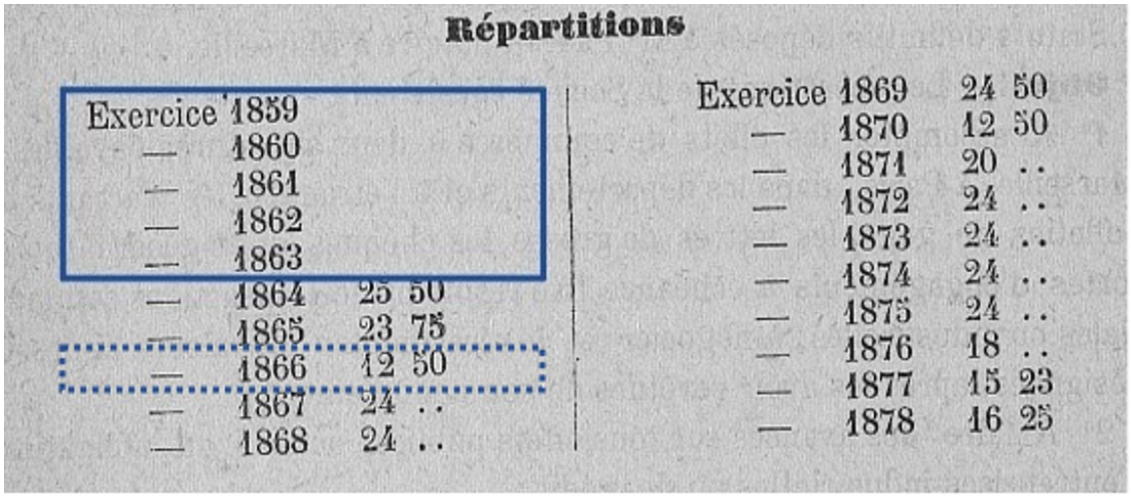
  - Individual projects, silo knowledge, no metadata standards

Example: Incomplete or Conflicting information



Répartitions

Exercice	1859	
—	1860	
—	1861	
—	1862	
—	1863	
—	1864	25 50
—	1865	23 75
—	1866	12 50
—	1867	24 ..
—	1868	24 ..
Exercice	1869	24 50
—	1870	12 50
—	1871	20 ..
—	1872	24 ..
—	1873	24 ..
—	1874	24 ..
—	1875	24 ..
—	1876	18 ..
—	1877	15 23
—	1878	16 25

Répartitions annuelles aux actions.

Exerc.	Répartitions. fr.	0/0
1859.....	2.50 ou	4 »
1860.....	11 » —	8.80
1861.....	11 » —	8.80
1862.....	10.85 —	8.68
1863.....	19 » —	15.20
1864.....	25.50 —	20.40
1865.....	23.75 —	19 »
1866.....	23 » ou	18.40
1867.....	24 » —	19.20
1868.....	24 » —	19.20
1869.....	24.50 —	19.60
1870.....	12.50 —	10 »
1871.....	20 » —	16 »
1872.....	24 » —	19.20

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  - data of different types (quantitative as well as qualitative)
  - from different historical sources,
- hence, achieving extensibility.

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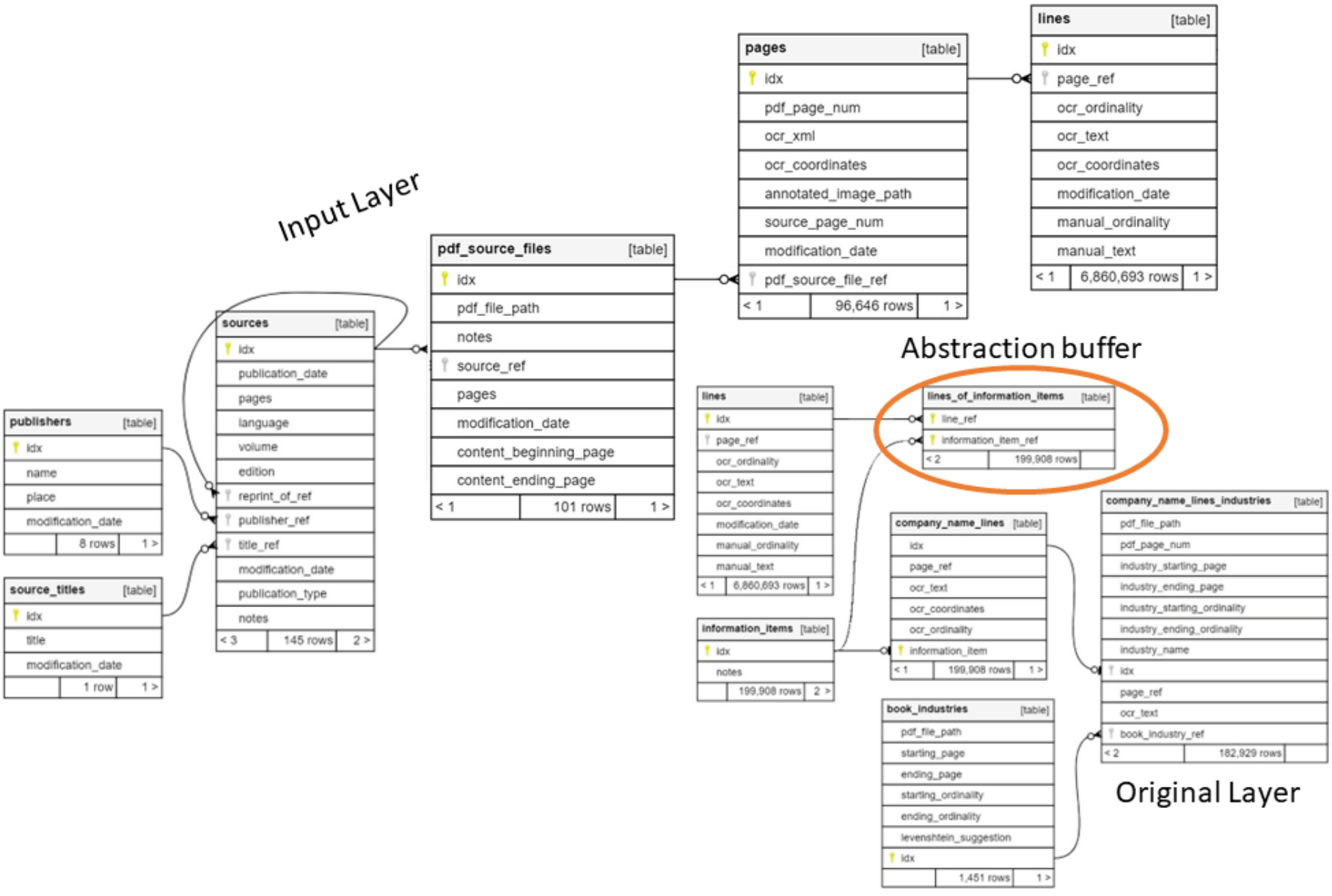
- Our implementation allows researchers to validate the digitized data against the original sources.
- A detailed description of the data model can be found in Gram *et al.* (2022).

Data Model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Original Layer
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ending_page
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ending_ordinality
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industry_ending_page
industry_starting_ordinality
industry_ending_ordinality
industry_name
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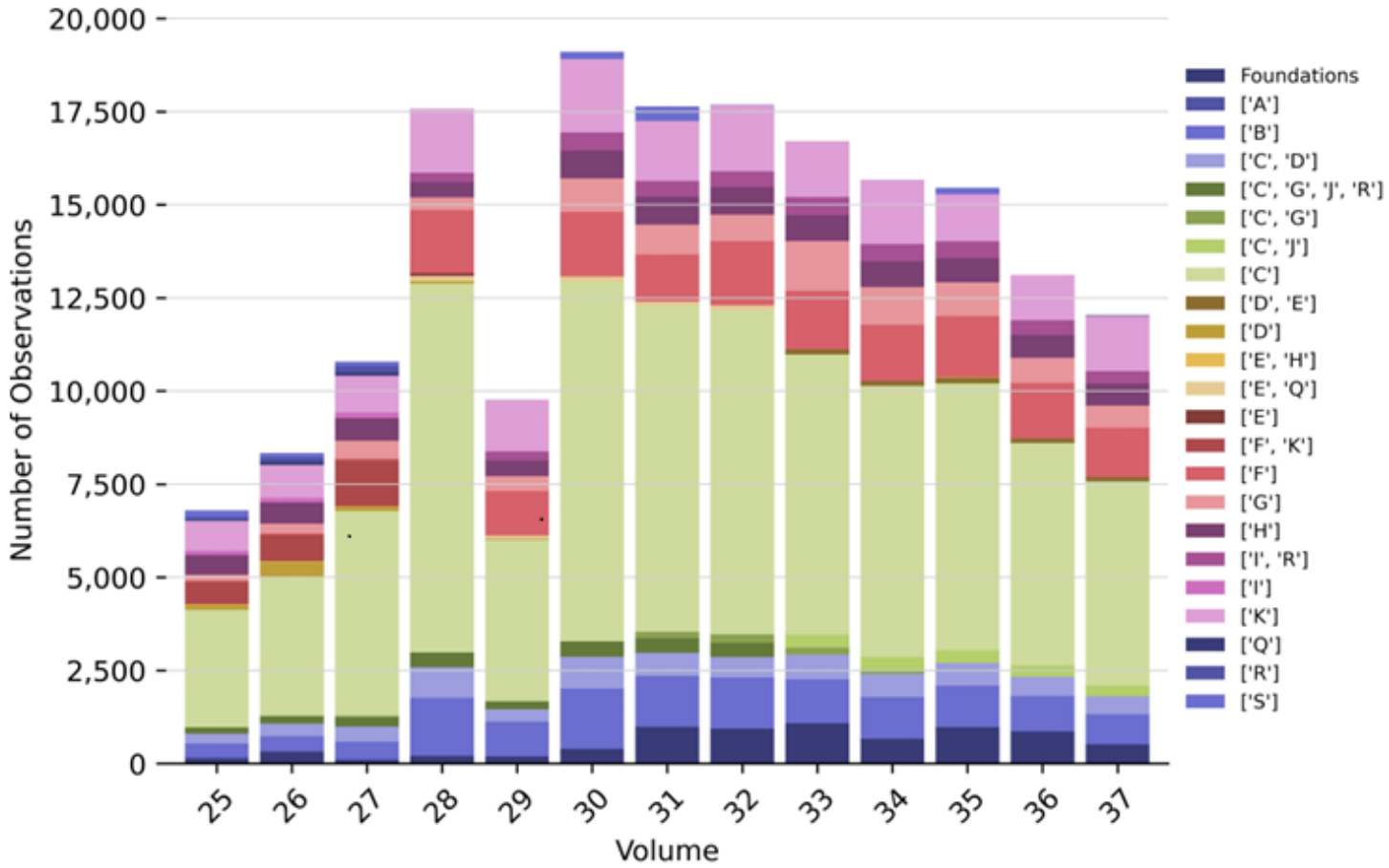
ocr_text
book_industry_ref
< 2 182,929 rows

Firm Industry Distribution per Volume

NACE Rev. 2 Section	Description
A	Agriculture, Forestry and Fishing
B	Mining and Quarrying
C	Manufacturing
D	Electricity, Gas, Steam and Air Conditioning
E	Water Supply, Sewerage, Waste Management and Remediation Activities
F	Construction
G	Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles
I	Accomodation and Food Service Activities
H	Transportation and Storage
J	Information and Communication
K	Financial and Insurance Activities
L	Real Estate Activities
M	Professional, Scientific and Technical Activities
N	Administrative and Support Service Activities
O	Public Administration and Defence; Compulsory Social Security
P	Education
Q	Human Health and Social Work Activities
R	Arts, Entertainment and Recreation
S	Other Service Activities
T	Activities of Households as Employers; Undifferentiated Goods- and Services-Producing Activities of Households for Own Use
U	Activities of Extraterritorial Organisations and Bodies



Validate against the original data sources

Lübecker Maschinenbau-Ges. in Lübeck, Direktion

- Digitized data (taken from input layer)
  - {Coup.-V.:,4,J.,(K.), Direktion:,Carl,"Mette","Emil,Wischow.}
- Derived data for information item Direktion (original layer)
  - Carl Mette, Emil Wischow

Lübecker Maschinenbau-Ges. in Lübeck, Prokuristen

- Digitized data (taken from input layer)
  - {Prokuristen:,H.,"Kaeferstein,",Chr.,"Behrens,",W.,"Priegnitz,",E.,"Tscha
- Derived data for information item Prokurist (original layer)
  - H. Kaeferstein, Chr. Behrens, W. Priegnitz, E. Tscharncke, Paul Flitner

Re-Structuring

Marius Liebald

Data Extraction Logic

- Line type recognition
  1. Line types definition
  2. Random forest classifiers using layout features & string similarities
  3. ANN classifier using
     - random forest predictions (probabilities)
     - contextual features
- Line collapsing
  0. Non-content line removal
  1. Assign lines to items
  2. Assign items to companies
  3. Assign companies to industries
- Variable parsing
  - Variable specific
  - Useful functions stored in folder
    - string_decomposer
    - date_detection
- Linking (i.e., Matchting)

Line types defintion

1454 Leder-Fabriken.

Leder-Fabriken.

Aachener Lederfabrik, Akt.-Ges. in Aachen.

Gegründet: 10./5. 1898; eingetr. 8./7. 1898. Statutänd. 6./7. 1899, 19./9. 1903, 24./10. bezw. 6./12. 1904, 20./10. 1905 u. 23./5. 1907. Übernahmepreis M. 1 123 000. Gründung s. Jahrgang 1902/1903. Die Firma lautete bis 6./12. 1904 „A.-G. für Lederfabrikation de Hesselle & Cie."

Zweck: Fabrikation von Leder aller Art, insbesondere von Riemencroupons, Sohlledercroupons, Vachecroupons u. Vacheabfällen. — Das Unternehmen wird auf dem der Ges. gehörigen, in der Jülichstr. 236 zu Aachen belegenen Grundstück betrieben, dasselbe ist 1 ha 5 a 52 qm gross und vollständig lastenfrei. Bebaut sind rund 5500 qm. Zu den eingebrachten Immobil. gehört auch eine Wassergerechtsame. Die Ges. beschäftigt durchschnittlich 140

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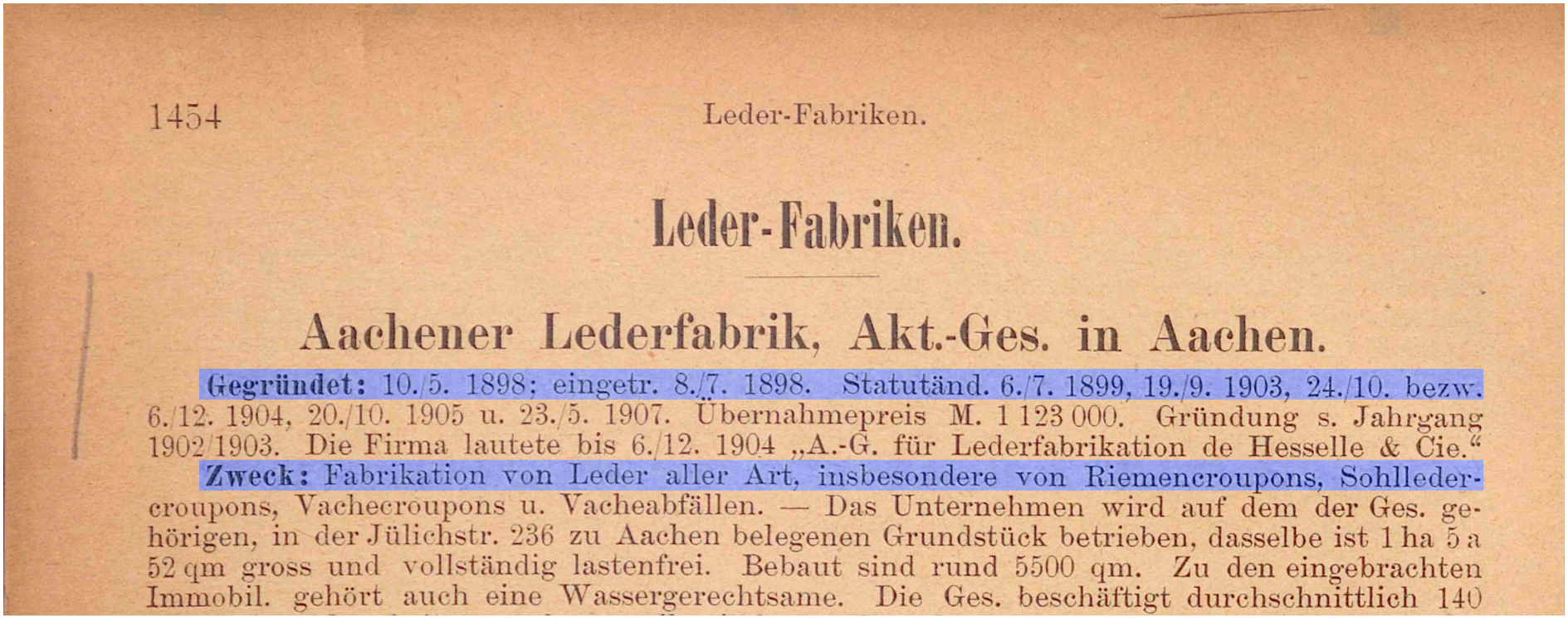

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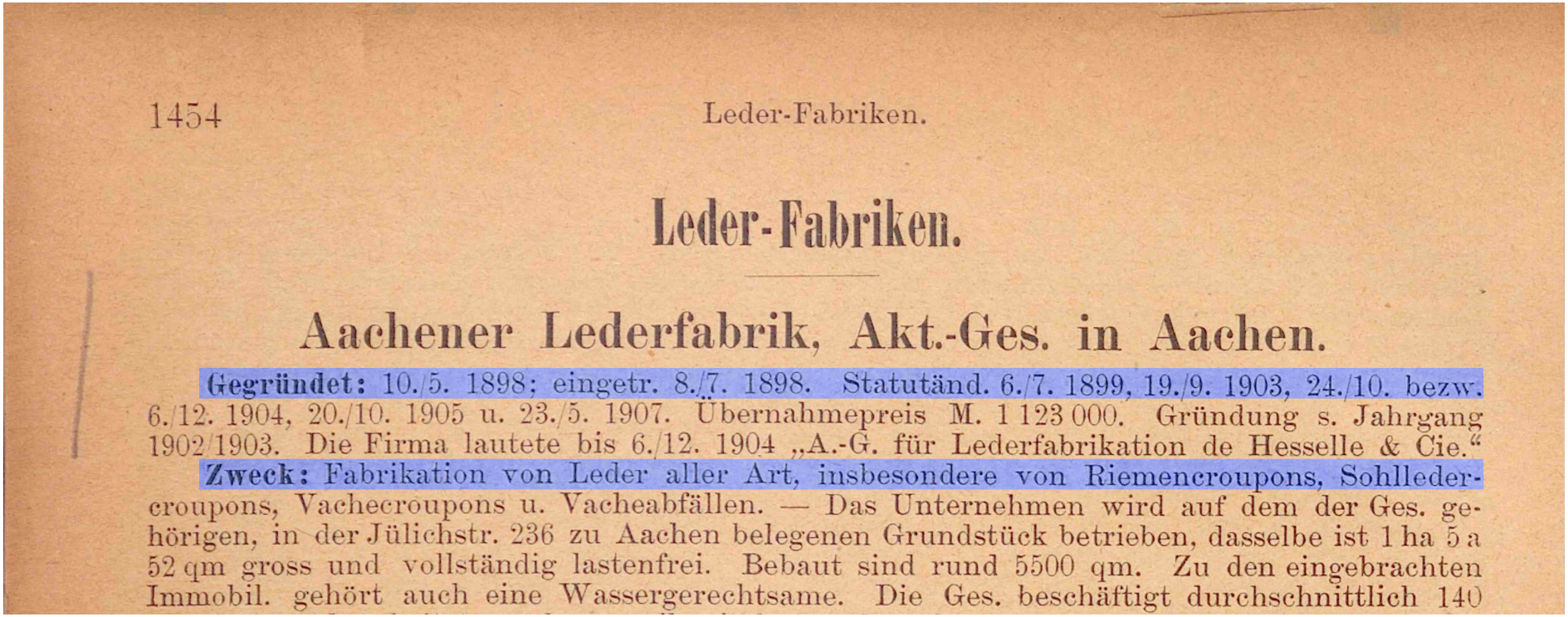

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→ In total, 19 different line types

Layout variables

- (line) textbox width
- (line) textbox center
- (line) textbox height
- (line) textbox height-width ratio
- **vertical distance to (line) textbox above/below**
- **avg. (word) textbox height**
- share of alphabetical characters
- share of non-alphanumerical characters
- **string distance to any industry**
- string distance to any item
- ...

One random forest classifier per line type (and document)

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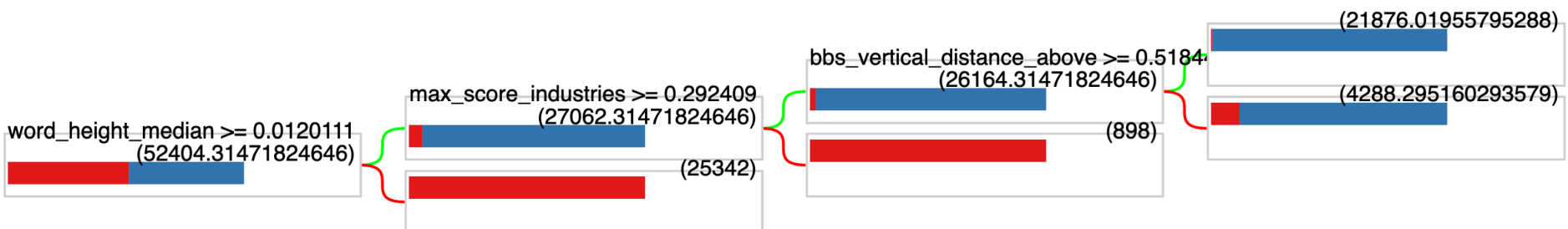

ANN classifier

Random forest prediction output

- For each line: one probability score for each line type
- Probability scores range between 0 and 1

ANN classifier input (for line i)

- random forest prediction $_{i+n}$ $\forall n \in [-5, 5]$
- for instance
  - if $n = 0 \rightarrow$ prediction of line i
  - if $n = 1 \rightarrow$ prediction of line below line i
  - if $n = -1 \rightarrow$ prediction of line above line i

Direktion: Rud. Türk. **Prokuristen:** Fabrik-Direktor A. Rommeney; Kassierer Max Diessler, Fritz Best.

Aufsichtsrat: (3—7) Vors. Rentier Arthur Pekrun, Weisser Hirsch; Stellv. Bank-Dir. Max Gentner, Rechtsanw. Dr. Elb, Dresden; Komm.-Rat Fr. Lindemann, Halberstadt; Dir. Curt Fochtmann, Meissen.

Zahlstellen: Eigene Kassen; Dresden u. Wernigerode: Mitteldeutsche Privatbank; Wernigerode: Heinr. Schmidt; Halberstadt: Mooshake & Lindemann. *

Gust. Schaeuffelen'sche Papierfabrik in Heilbronn a. N.

Bilanz am 30. Juni 1909: Aktiva: Immobil. 1 161 111, Masch. 664 711, Vorräte 594 737, Bar 2596, Wechsel 27 361, Effekten 6500, Debit. 366 282. — Passiva: A.-K. 857 142, R.-F. 40 017, Einlagen 459 481, Hypoth.-Anleihen 1 100 000, Kredit. 339 913, Gewinn 26 745. Sa. M. 2 823 301.

Gewinn- u. Verlust-Konto: Debet: Betriebsausgaben 1 429 120, Gewinn 26 745. Sa. M. 1 455 865. — Kredit: Betriebseinnahmen M. 1 455 865.

Direktion: Carl Schaeuffelen, G. Hub. **Aufsichtsrat:** Vors. A. Schmidt.

Cellulose-Fabrik Hof in Hof-Moschendorf.

Gegründet: 29./6. 1892 durch Übernahme der Fabrik Wiede & Co. in Moschendorf für M. 450 000. Letzte Statutänd. v. 28./4. 1900.

Zweck: Herstellung von Cellulose und damit in Zus.hang stehender Fabrikate.

Kapital: M. 450 000 in 450 Aktien à M. 1000.

1. Assign lines to items
2. Assign items to companies
3. Assign companies to industries

Useful functions

```
class Common_operations():
        def __init__(self):
                pass

        def string_decomposer(self, string:str, comp_regex:dict):
                """
                [...]
                """

        def date_detection(self, string:str, extract=True, replace=True):
                """
                [...]
                """
```

string_decomposer()

```
example_pl = """
        Gewinn- u. Verlust-Konto: Debet: Item A 111,
        Item B 222. - Kredit: Item C 333, Item D 444. Sa. M. 777.
        """

result = Common_operations().string_decomposer(
        string= example_pl,
        comp_regex = {'debet':['Debet:'], 'kredit' : ['Kredit', 'Credit:'],
                'sum':['Sa\.?\s?M\.?']}
        )

print(result)
        {
        'debet': 'Item A 111, Item B 222. -',
        'kredit': ': Item C 333, Item D 444.',
        'sum': '777.',
        'begin': 'Gewinn- u. Verlust-Konto:'
        }
```

date_detection()

```
example_str = """Mein Geburtstag ist am 3. Aug. 1990.
Der Meiner Nichte am 8./7. 2020"""

result = Common_operations().date_detection(
        string = example_str,
        extract = True,
        replace = False
        )

print(result)
(
'Mein Geburtstag ist am 3. Aug. 1990. Der Meiner Nichte am 8./7. 2020',
[datetime.date(1990, 8, 3), datetime.date(2020, 7, 8)]
)
```

Linking

Pantelis Karapanagiotis

Matching Data is Hard

- Adam et al., 2021 . Data extraction and matching The EurHisFirm experience. Methodological Advances in the Extraction and Analysis of Historical Data.
- Cule et al., 2020 . Data Connecting Case Study (EurHisFirm M6.2).
- Poukens, 2018 . Report on the Inventory of Data and Sources (EurHisFirm D4.2).
- Karapanagiotis, 2019 . Technical document on national data models (EurHisFirm D5.1).

Can we Develop Reusable Tools?

User requirements:

1. meaningful match suggestions

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1. meaningful match suggestions
2. in reasonable execution time

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3. using information from multiple entity characteristics

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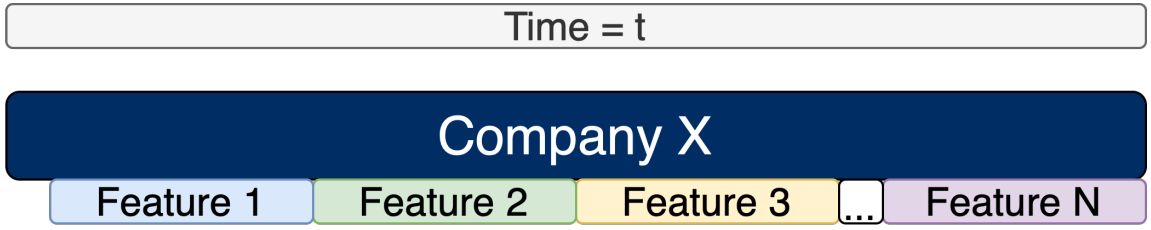
4. applicable in different matching contexts

Can we Develop Reusable Tools?

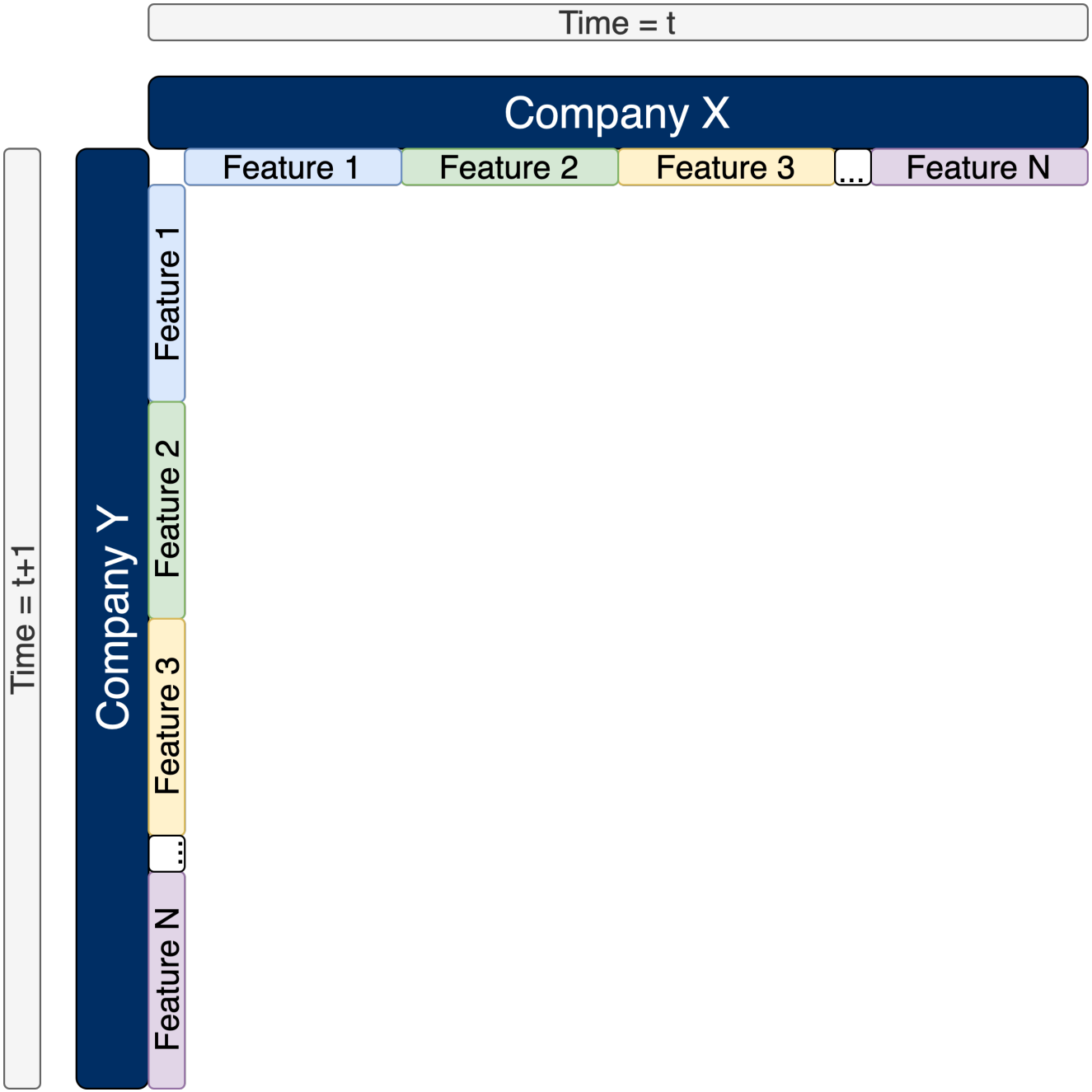
User requirements:

1. meaningful match suggestions
2. in reasonable execution time
3. using information from multiple entity characteristics
4. applicable in different matching contexts
   - in particular for heterogeneous country data

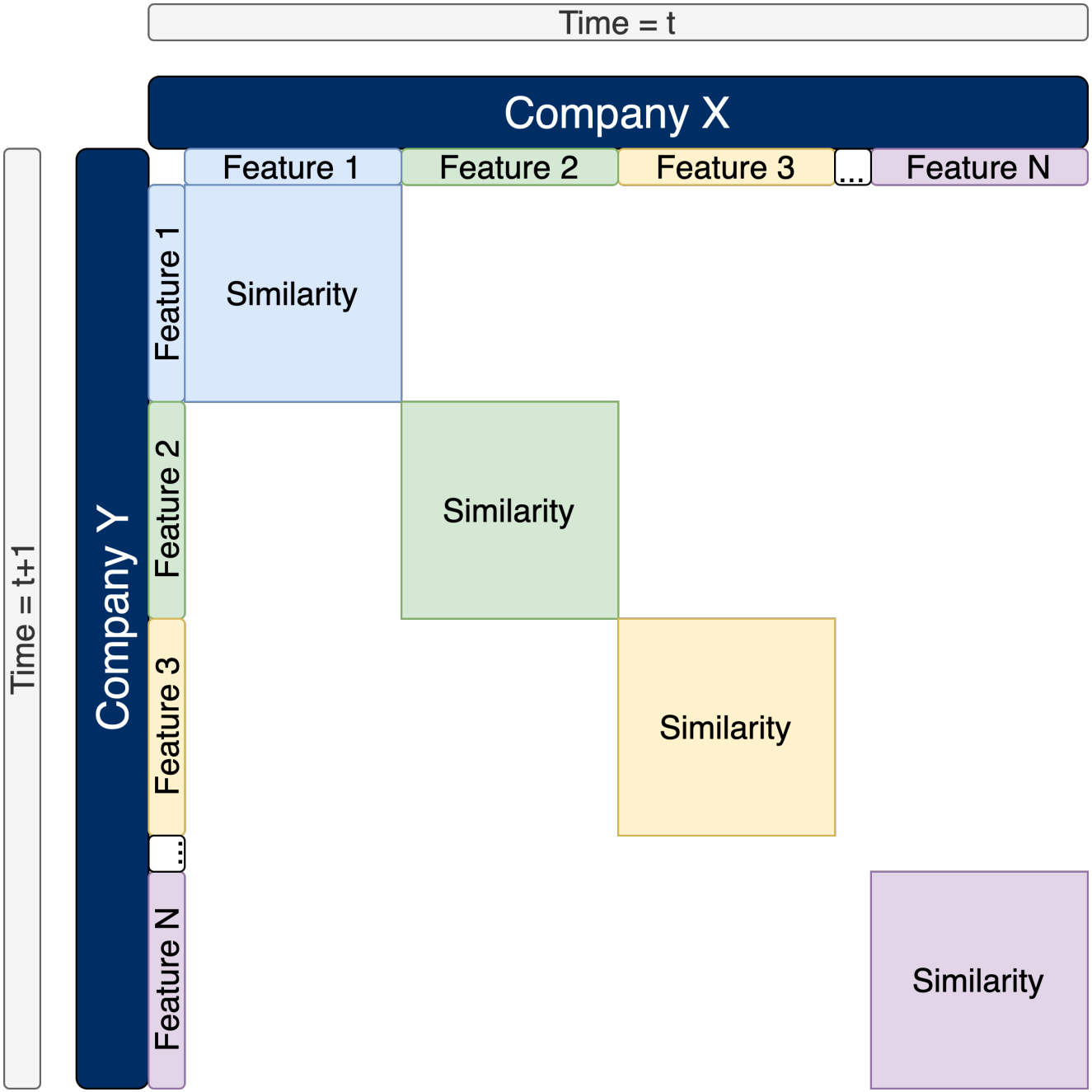
A Matching Problem Example



A Matching Problem Example



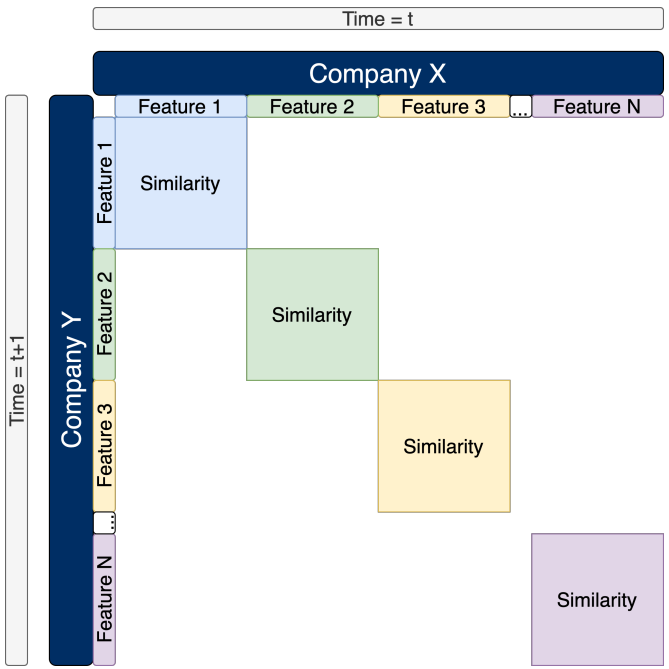
A Matching Problem Example



A Matching Problem Example

Using multiclass classification

- Use the firms of Right as output classes.
- Train a model to classify each f_l from *Left* to one of the output classes.
- But:
  - Say, *Right* is the master database.
  - It gets updated and now contains additional firms.
  - The model will not give classification probabilities for the new firms.



Matching as a Binary Classification Problem

- Instead, we can approach the problem from another perspective.
- Make pairs of records for each firm f_l in the *Left* and f_r in the *Right* data.
- Classify the pairs (f_l, f_r) as a match $label = 1$ or no match $label = 0$.
- But:
  - This requires cross-joining the *Left* and *Right* data.
  - The memory requirements to store the transformed data can quickly render the solution infeasible.
  - Even for small data sources, say $N_L = 5 \cdot 10^3$ and $N_R = 10^4$, the matching pairs $N_{LM} = 5 \cdot 10^7$ require 100s of Gb.

Matching with Blocking

- One solution is to use blocking (Doll et al., 2021).
- Exclude some potential pairs based on pre-defined criteria before training.
- E.g., match *Left* with firms from *Right* that have the save foundation year.
- This effectively reduces the memory requirements problem.
- But:
  -
  - The blocking criteria require having already expertise with the data,
  - are not re-usable in different contexts, and
  - might even be different for heterogeneous country data.
- Can we do better?

Matching with a Similarity Encoder

- Encoders are used in natural language processing models (see e.g. Vaswani et al., 2017).
- They reduce text data to vectors used to train models.
- These models use a huge amount of data.
- The encoding is calculated on the fly.
- How can we use this idea?

Matching with a Similarity Encoder

Using a similarity encoder

1. Pick a pair (f_l, f_r) of *Left* and *Right* firms.

Matching with a Similarity Encoder

Using a similarity encoder

1. Pick a pair (f_l, f_r) of *Left* and *Right* firms.
2. Instruct how the features of f_l and f_r are associated.

Matching with a Similarity Encoder

Using a similarity encoder

1. Pick a pair (f_l, f_r) of *Left* and *Right* firms.
2. Instruct how the features of f_l and f_r are associated.

```
similarity_map = {
    "company_name": {
        "discrete": discrete_si
        "partial": partial_ratio
    },
    "address": {
        "partial": partial_ratio
    },
    "purpose": {
        "sort": token_sort_ratio
    },
    "foundation": {
        "discrete": discrete_si
        "partial": partial_ratio
    },
}
```

Matching with a Similarity Encoder

Using a similarity encoder

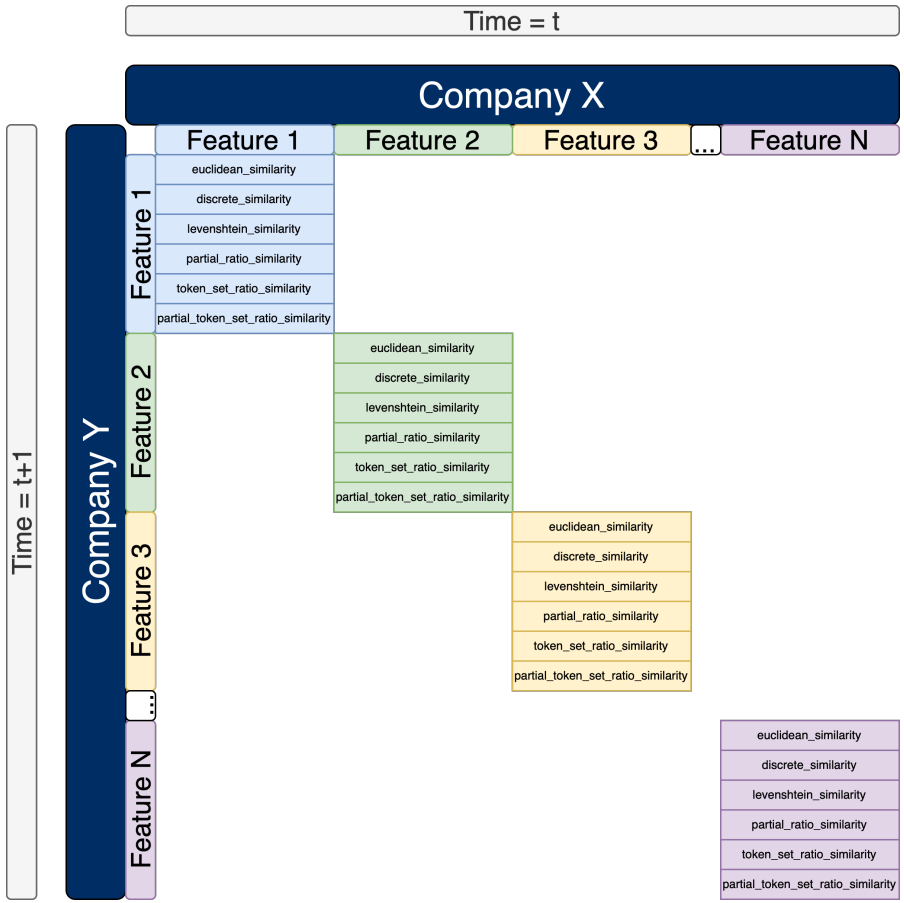
1. Pick a pair (f_l, f_r) of *Left* and *Right* firms.
2. Instruct how the features of f_l and f_r are associated.

```
similarity_map = {
    ...
    "address<->address1": {
        "partial": partial_rati
    },
    "address<->address2": {
        "partial": partial_rati
    },
    ...
}
```

Matching with a Similarity Encoder

Using a similarity encoder

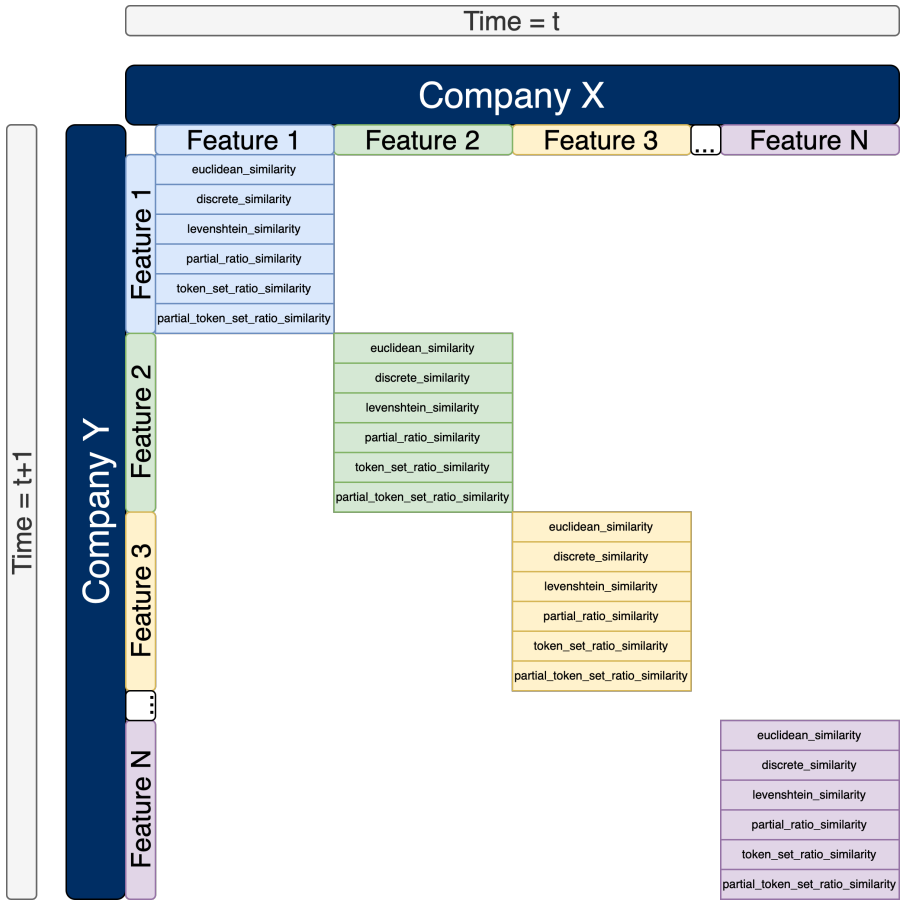
1. Pick a pair (f_l, f_r) of *Left* and *Right* firms.
2. Instruct how the features of f_l and f_r are associated.
3. Calculate various similarities for each feature on the fly.



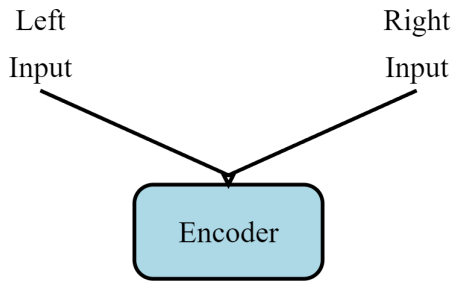
Matching with a Similarity Encoder

Using a similarity encoder

1. Pick a pair (f_l, f_r) of *Left* and *Right* firms.
2. Instruct how the features of f_l and f_r are associated.
3. Calculate various similarities for each feature on the fly.
4. Train the binary matching model using these similarities.



Network Architecture



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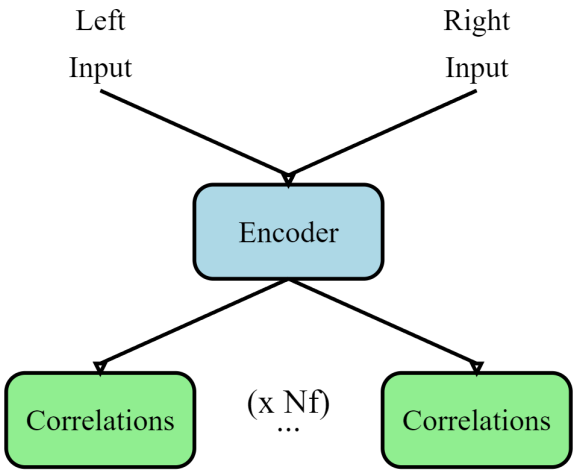

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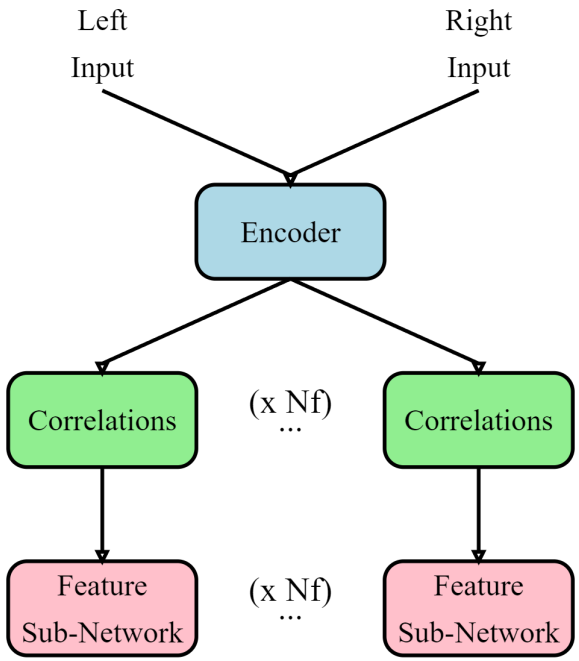

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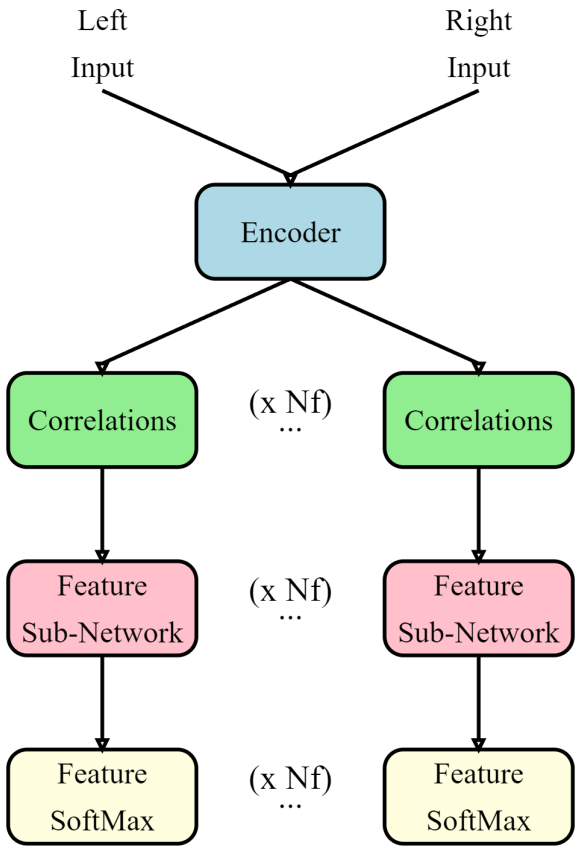

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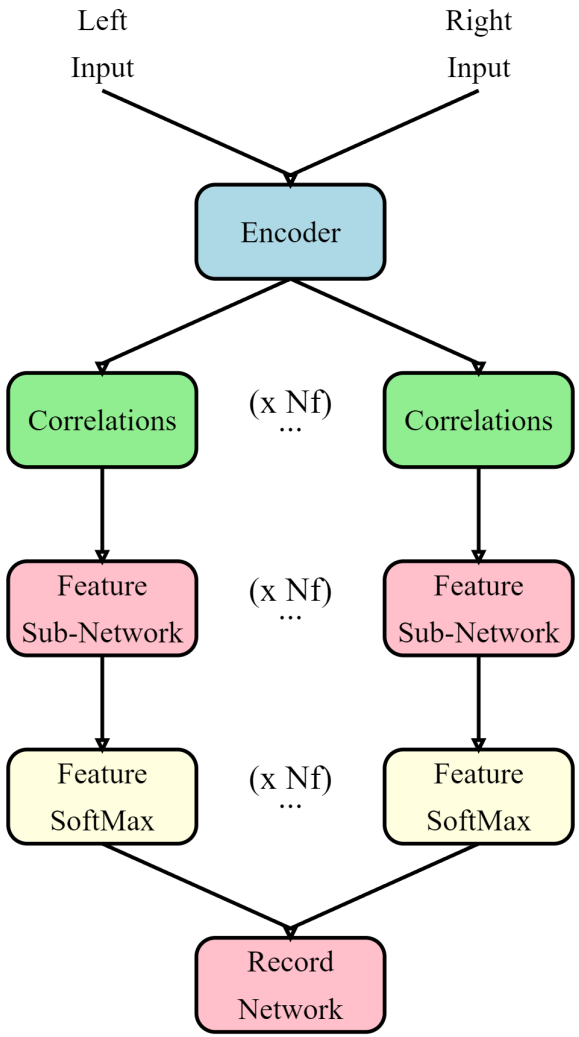

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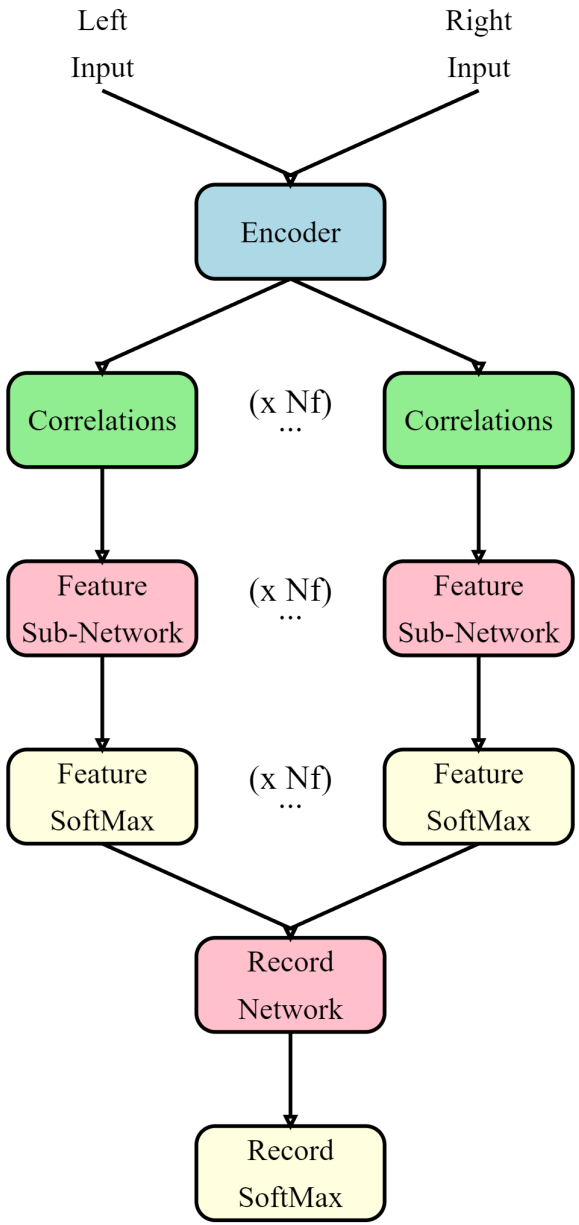
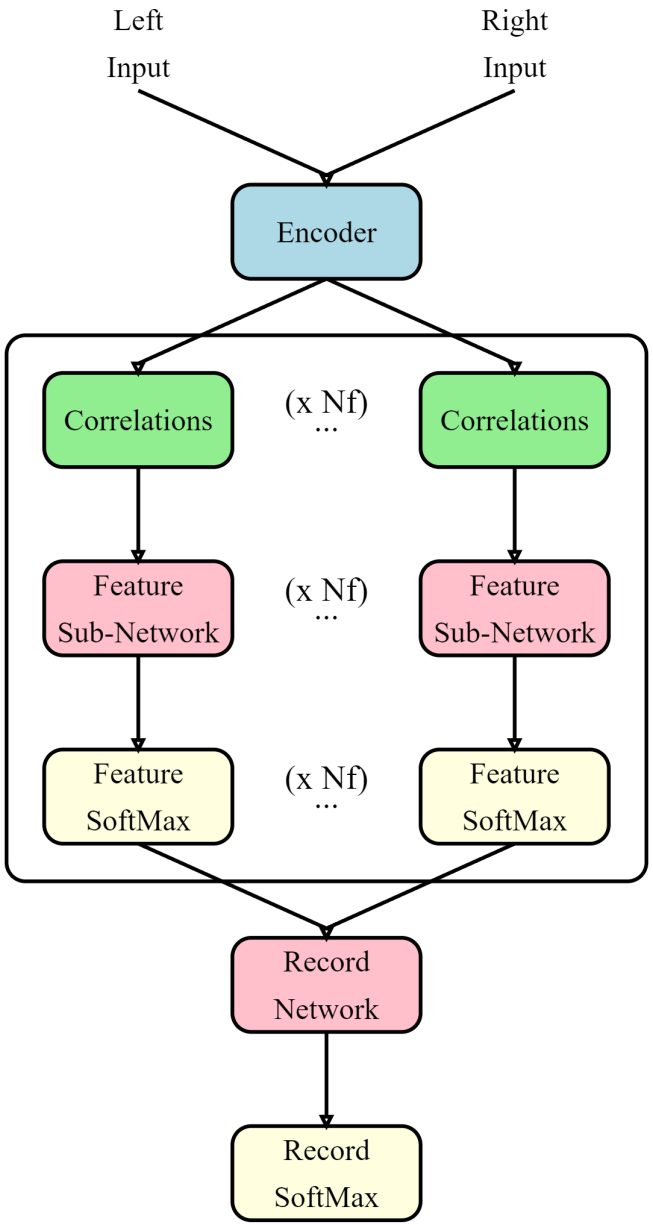


Network Architecture



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model = match.MatchingModel(similarity_map)
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    metrics=evaluation_metrics
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train_evaluation = model.evaluate(train_left, train_rig

predictions = model.predict(train_left, train_right)
suggestions = model.suggest(train_left, train_right, 3
```

Bibliography

Gram, D., Karapanagiotis, P., Liebald, M. and Walz, U. (2022). Design and implementation of a historical german firm-level financial database. *J. Data and Information Quality*, **14** (3).