

# PPDS - Duplication detection

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## 1. Introduction

#### 1.1 Definition

## **Duplication Detection**



"Detection method for detecting **similar** or **one to one** entries in a Database"



- 10 % of customer records are duplicates

## Origin:

- Entry errors: Typographical / Inconsistent formatting / Humans errors
- Data integration: Merging / Integrating / Unification

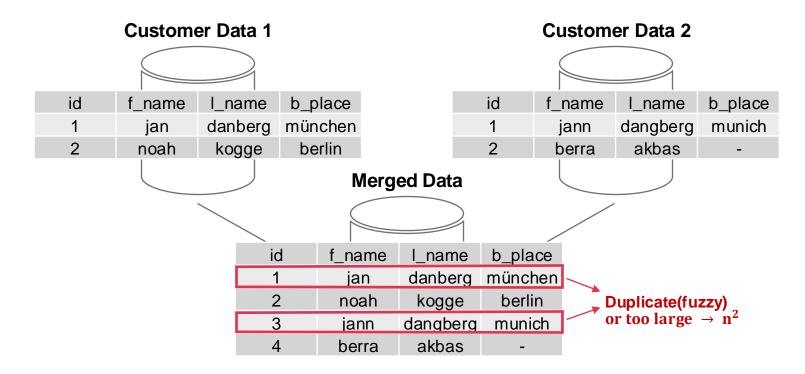
## Problems:

- Data quality issues: Accuracy / Inconsistency
- Perfomance degradation: Query performance / System overhead



## 2. Problem Statement

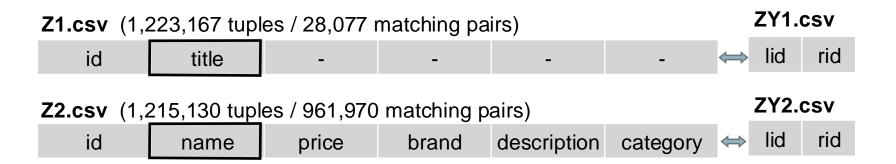
### 2.1 Main issues in duplication detection





## 2. Problem Statement

#### 2.2 Task Overview



### <u>Infrastructure:</u>

- def generating\_blocking\_key(row: Series) → distinctive, clean
- def create\_blocks(input\_df: DataFrame)
- def create\_matches(blocks: dict, input\_df: DataFrame)



### 3.1 Data preprocessing



"Identify important / dominant patterns (e.g. sellers, brand, device etc)"



### 3.1 Data preprocessing

id	title
1	"Dell dell netbook. 12.24 400GB 20Ram tech bui, eBay  - "13@insane cndition"



Text standardization (A-Z → a-z, (-,|,@,") → (´´), good → (´´))
Error correction(bui → buy, cndition → condition)
↓
Semantic mapping (insane / perfect / awesome → good)



id	title
1	dell netbook 400gb 20ram ebay



- 3.2 Blocking- and Ascii key generation
- Pattern initialization:

```
'brands': re.compile(r'\b(acer|panasonic|toshiba|hp|sony|lenovo')
```

Attribute extraction:

```
def find_brands(text: str) -> str:
    if patterns['brands'].findall(text):
        return " ".join(sorted(set(patterns['brands'].findall(text))))
    else:
        return ''
```

## Example:

```
text1 = "lenovo dell tablet good quality c23423c23542"
result1 = find_brands(text1)
print(f"Text 1 Brands: '{result1}'") # Ausgabe: 'dell lenovo'
```



3.2 Blocking- and Ascii key generation



```
def generate_blocking_key_name(row: pd.Series) -> tuple:
    # Convert the title to a string and lowercase
    title = str(row['title'])
    low_title = title.lower()

# Initialize dictionaries to store patterns and corresponding row indices
pattern2id_1 = defaultdict(list)

# Generate initial blocking key based on sorted words in the title
pattern2id_1[" ".join(sorted(low_title.split()))].append(row.name)

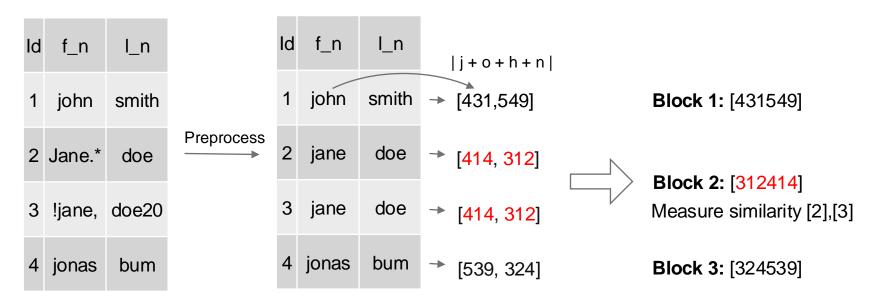
# Extract brands from the cleaned title
brands = find_brands(low_title)
if brands:
    pattern2id_1[brands].append(row.name)
```

return pattern2id\_1 → add more blocking keys



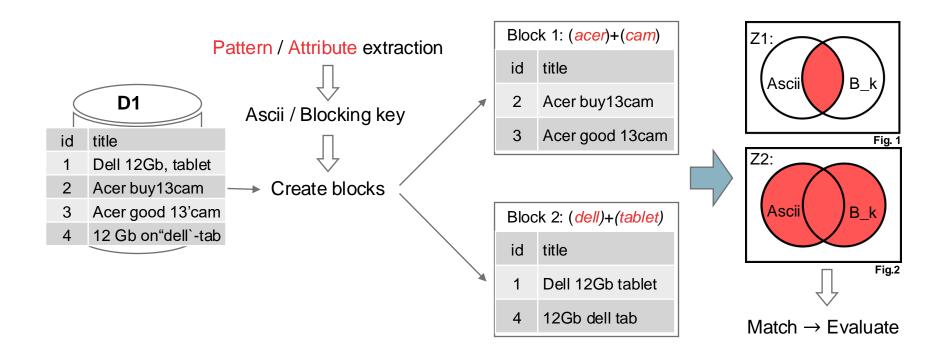
### 3.2 Blocking- and Ascii key generation

## Ascii key:



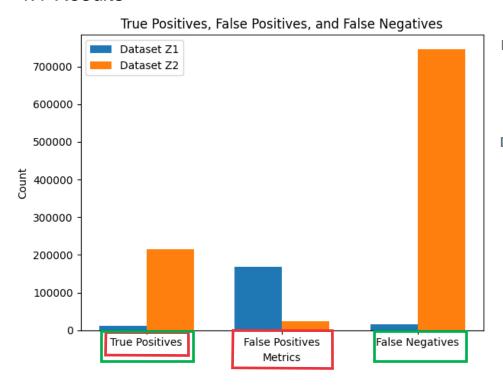


## 3.3 Summary





### 4.1 Results



## Environment:

Device: MacBook ProChip: Apple M3 Pro

- Memory: 18 GB

## Benchmarks:

	<b>Z</b> 1	<b>Z2</b>
Jac_sim	0.8	0.75
Precision	0.07	0.90
Recall	0.45	0.22
F1 Score	0.12	0.36
Time total	2214.0	63 sec



### 4.1 Results

	<b>Z</b> 1	<b>Z2</b>		
Jac_sim	0.8	0.75	Manually Adjusted (dependent on the dataset)	
Precision	0.07	0.90	Patterns too broad, capturing all potential matches  Patterns too narrow, covering small subset  Improvements:	
Recall	0.45	0.22		
F1 Score	0.12	0.36		
Time total	2214.0	63 sec	<ul> <li>Z1: Precise blocking keys (reduce false positives)</li> <li>Z2: Broaden blocking patterns (reduce false negatives)</li> </ul>	



#### 4.1 Result

## **Observation:**

695913, PANSONIC ASPIRE LENOVO VOLOGY 15.6 DUO EDEN 2GB 17 | 10.1 17 NVIDIA 2.60 (4

765460, Pansonic Aspire Lenovo Vology 15.6 Duo Eden 2GB i7 | 10.1 17 NVIDIA 2.60 (4

684204, "Lenovo VivoBook - Mobile 17 14"" Edition"

988519, "LENOVO VIVOBOOK - MOBILE 14"" EDITION"

Detected but not provided in ground truth

Precision for 71 cannot be increased





#### 4.2 Reflection

### Takeaway:

- **Balance** between recall, precision and similarity thresholds
- Improve blocking strategies (Combine more keys, relaxing key criteria)
- Enhance scalability (Progressive classification, different similarity joins or ML)

## Our issues:

- **Definition** of **duplicate** (Dataset-dependent, fuzzy duplicates)
- Perfect **preprocessing** (Denoise entries universally, regex extraction, limitations)
- Function testing (Inapplicable on whole dataset due to inconsistencies)
- Dominant pattern filtering (Extraction of most frequent occurring attributes)





## 5. References

#### Fig 1,2

- https://de.wikipedia.org/wiki/Mengenlehre (last visited: 25.06.2024)
- <a href="https://dbgroup.ing.unimore.it/sigmod22contest/leaders.shtml">https://dbgroup.ing.unimore.it/sigmod22contest/leaders.shtml</a> (last visited: 01.07.2024)
- https://mboehm7.github.io/teaching/ss24\_ppds/05\_Experiments.pdf (last visited: 02.07.2024)
- <a href="https://bigdama.github.io/teaching/teaching\_materials/01\_Introduction\_D2IP.pdf">https://bigdama.github.io/teaching/teaching\_materials/01\_Introduction\_D2IP.pdf</a> (last visited: 04.07.2024)
- <a href="https://bigdama.github.io/teaching/teaching\_materials/02\_Duplicate\_Detection.pdf">https://bigdama.github.io/teaching/teaching\_materials/02\_Duplicate\_Detection.pdf</a> (last visited: 03.07.2024)
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