## Machine learning approach to cross-device identification of users

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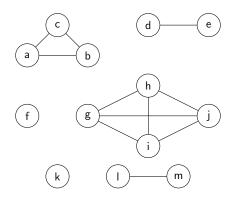
IT Research Workshop at WCC 2018, Poznań, September 21, 2018

#### **Cross-identification of users**



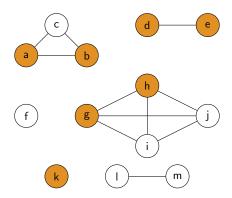
• Applications: Online advertising, content management and personalization, fraud detection.

#### Graph representation of users and devices



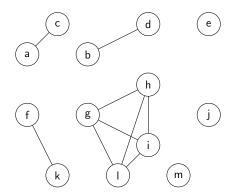
- nodes: devices (e.g., a, b, c, d, e, ...)
- cliques: users with their devices (e.g., (a,b,c))

#### **Deterministic cross-device graphs**

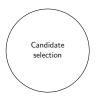


- Unique factors to identify a person, e.g., email address or login name
- Quality far beyond from being perfect!
- Used for training and evaluating probabilistic solutions

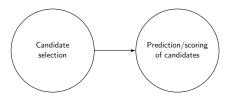
#### Probabilistic cross-device graphs



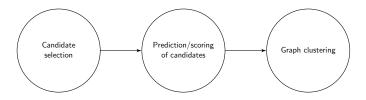
- Based on deep analysis of logs (behavior of devices in the Internet)
- Hand-made rule vs. Data-driven approach ( $\Rightarrow$  Machine learning)



• Candidate selection: reducing the number of possible pairs by filtering them by some initial premises

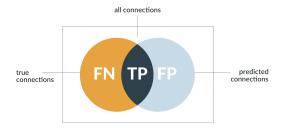


• Prediction/scoring: estimating the score for each candidate pair of devices



• Graph clustering: construction of the probabilistic graph

#### Measuring performance of cross-device solutions



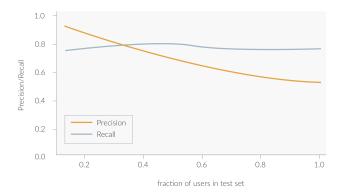
• Precision and recall:

$$\begin{aligned} \text{Recall} &= P(\hat{y} = 1 | y = 1) = \frac{P(y = 1, \hat{y} = 1)}{P(y = 1)} = \frac{\text{TP}}{\text{TP} + \text{FN}} \,, \\ \text{Precision} &= P(y = 1 | \hat{y} = 1) = \frac{P(y = 1, \hat{y} = 1)}{P(\hat{y} = 1)} = \frac{\text{TP}}{\text{TP} + \text{FP}} \,, \end{aligned}$$

#### where

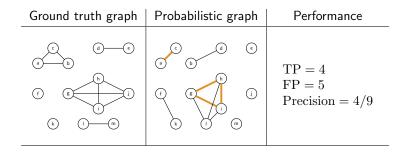
- ▶  $y = 1 \Rightarrow$  there exists a true connection between two devices,
- $\hat{y} = 1 \Rightarrow$  a connection has been predicted in the graph.

#### Pitfalls of the commonly used methodology

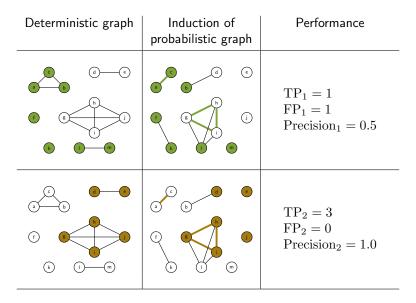


- Recall relatively stable with the size of deterministic graph
- Precision decreases with the size of deterministic graph (overestimation)!

#### Why precision decreases?



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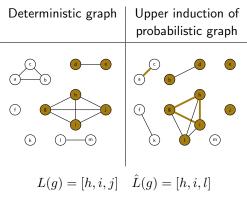
 $TP = 4 = TP_1 + TP_2$   $FP = 5 \neq FP_1 + FP_2$  Precision = 4/9

• Induction of probabilistic graph:

| Deterministic graph | Lower induction of probabilistic graph | Upper induction of probabilistic graph |
|---------------------|--|--|
|                     |  |  |

These two types of induction give the lower and upper bound of the value of precision.

- Device-based measures:
  - For each device  $v \in V$  construct two lists:
    - L(v): list of devices connected with v in deterministic graph,
    - $\hat{L}(v)$ : list of devices connected with v in probabilistic graph.



- Device-based measures:
  - ► The performance is then averaged over single devices:

$$M_V = \frac{1}{|V|} \sum_{v \in V} M_v(L(v), \hat{L}(v)).$$

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•  $M_v$  can be defined, for example, as a device-based recall and precision:

$$\begin{aligned} \operatorname{Recl}(L(v), \hat{L}(v)) &= \quad \frac{|L(v) \cap \hat{L}(v)|}{|L(v)|} \,, \\ \operatorname{Prec}(L(v), \hat{L}(v)) &= \quad \frac{|L(v) \cap \hat{L}(v)|}{|\hat{L}(v)|} \,. \end{aligned}$$

### Summary

- Cross-device identification actual and challenging problem.
- Machine learning approach to cross-device identification.
- Measuring performance of cross-device identification solutions.

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# Thank you

Q&A