Annotator agreement in the anonymization of court decisions

CL2021 in Limerick

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recorded on June 27, 2021



Why bother?

Legal documents are interesting!

- Publication of court decisions necessary for transparent legal system
- Electronic legal documents essential as training data for legal tech applications
- Corpus-linguistic research (e.g. terminology, comprehensibility, ...)

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- Compliance with constitutional data protection rights (i.a. GDPR)
- ⇒ Remove any information that might be used for de-anonymization

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Funding by the **Bavarian State Ministry of Justice** for research on the **automatic anonymization of court decisions**

Project and team

- **Goal**: Evaluation of the legal and technical issues concerning the ability to automatically anonymize (and pseudonymize) court decisions
- Interdisciplinary project: legal theory and methodology (guidelines), computational corpus linguistics (annotation, automatization)

CCL

- Prof. Dr. Stefan Evert
- Natalie Dykes
- Philipp Heinrich

Law School

- Prof. Dr. Axel Adrian
- Michael Keuchen

+ 4-8 student assistants

Tag set

direct identifiers

- names (natural and legal persons)
- addresses
- registration numbers
- dates of events

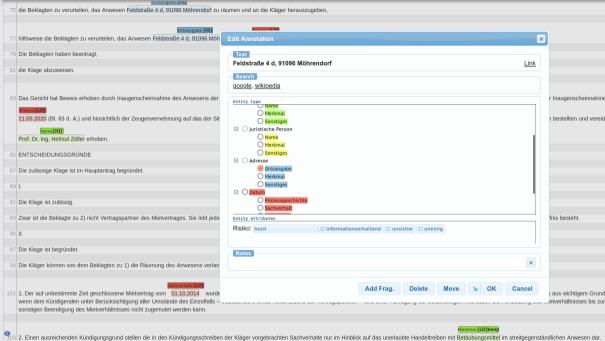
Tag set

direct identifiers

- names (natural and legal persons)
- addresses
- registration numbers
- dates of events

indirect identifiers

- profession details, academic titles, health conditions
- descriptive information about local conditions or companies
- unique features (e.g. the only red house in a small village)



Corpus & data

Tabular data analyzed here

- based on 513 verdicts
- law of tenancy and traffic law
- 917,163 tokens
- 24,972 sensitive text spans after adjudication
- columns:
 - document ID
 - character span (start, end)
 - category tag
 - risk level

Tags and risk assessment (selection)

	high	medium	low
address (indirect)	1	182	1046
address (exact)	2317	1127	1028
date (fact)	0	7	4212
date (process)	0	0	3704
formal (court)	0	0	2120
formal (reference number)	6	18	1833
legal person (indirect)	0	14	38
legal person (name)	51	695	27
natural person (indirect)	0	19	306
judges, lawyers, (name)	1765	2	228
natural person (name)	3333	0	2
car (indirect)	0	0	670
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- Restriction to selected categories: n = 15,005 sensitive text spans
- Focus on precision and recall
 - ▶ standard IAA measures (Cohen's κ , Krippendorff's α) problematic (overlaps)
 - here: annotator has successfully identified text span if their annotation (regardless of selected category) overlaps with the respective span in the adjudicated data

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- Naïve estimates for individual success probabilities (= recall)

will inevitably overestimate real recall

NB: annotator MP best, even when not the final adjudicator

A naïve statistical model

Assumptions

- a) coders only make random errors with probability of failure q = 1 p
- b) q = 1 p is the same for all text spans
- c) q = 1 p is the same for all coders
- d) errors made by the different coders on different items are independent

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Random variable

- N: number of coders needed until a given text span is found for the first time
- N = k: first k 1 coders have missed the span, but coder k has annotated it
- $N \sim \text{Geo}(p)$, i. e. for $k \in \{1, 2, ...\}$:

$$\mathbb{P}\{N=k\} = (1-p)^{k-1} \cdot p \text{ and } \mathbb{P}\{N \le k\} = 1 - (1-p)^k$$

Observable variables

definition

 I_k : number of text spans with N = k (found for the first time by k-th coder)

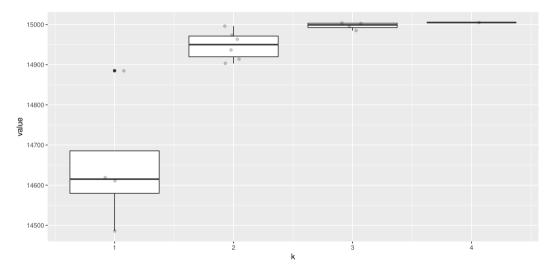
 C_k : number of text spans with $N \leq k$ (found by a set of k coders)

distribution

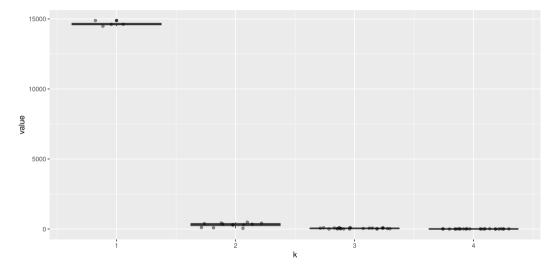
probabilites are equal for all spans and errors are assumed to be independent:

$$I_k \sim \operatorname{Bin}(n_0, \mathbb{P}\{N = k\})$$
 $C_k \sim \operatorname{Bin}(n_0, \mathbb{P}\{N \le k\})$ $\mathbb{E}[I_k] = n_0 \cdot \mathbb{P}\{N = k\}$ $\mathbb{E}[C_k] = n_0 \cdot \mathbb{P}\{N \le k\}$ $\mathbb{P}\{N = k\} = (1 - p)^{k-1} \cdot p$ $\mathbb{P}\{N \le k\} = 1 - (1 - p)^k$

Empirical distribution of C_k for $k = \{1, 2, 3, 4\}$

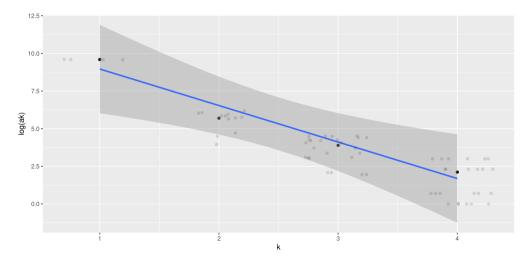


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Logarithmic y-axis, taking the means



Parameter estimation

$$I_k \sim \operatorname{Bin}\left(n_0, (1-p)^{k-1} \cdot p\right)$$

$$\mathbb{E}\left[I_k\right] = n_0 \cdot p \cdot (1-p)^{k-1}$$

$$\log\left(\mathbb{E}\left[I_k\right]\right) = \left[\log(n_0) + \log(p) - \log(1-p)\right] + \left[\log(1-p)\right] \cdot k$$

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- $\hat{p} \approx 91.15\%$
- $\hat{n}_0 \approx 8539.18$
- $\hat{\mathbb{E}}[I_5] \approx 0.48$

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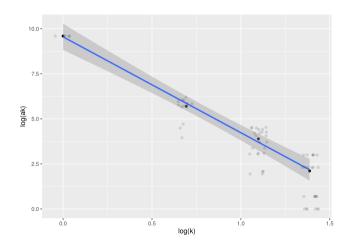
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however: not a perfect fit!

- estimates imply negative number of FNs ($\hat{n}_0 \ge n = 15{,}005$)
- individual success probability \hat{p} wildly underestimated

An allometric model inspired by the plot

Double-logarithmic axes



$$\log(\mathbb{E}[I_k]) = \log(t) + m \cdot \log(k)$$

$$\Leftrightarrow \mathbb{E}[I_k] = t \cdot k^m$$

- $\hat{p} \approx 97.19\%$
- $\hat{n}_0 \approx 14421.22$
- $\hat{\mathbb{E}}[I_5] \approx 2.68$
- $\hat{\mathbb{E}}[I_6] \approx 1.02$
- $\hat{\mathbb{E}}[I_7] \approx 0.49$

Conclusion

- Anonymization of sensitive legal documents (data protection)
- Here: 4-fold annotation by trained student assistants following detailed guidelines
- Estimation of expected false negatives to ensure annotation quality
- Interim result: 4-7 annotators sufficient
- Statistical model not entirely satisfying

Future work

- Individual success probability p_i for each annotator (\neq assumption c)
- ullet Correlations between annotators (eq assumption b / d)

	miss-miss	hit-miss	miss-hit	hit-hit
RB-LT	42	352	344	14267
RB-HS	102	417	284	14202
RB-MP	68	52	318	14567
LT-HS	91	428	303	14183
LT-MP	9	111	385	14500
HS-MP	31	89	488	14397

