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International developments in policy: Tools and workflows for sensitive data management

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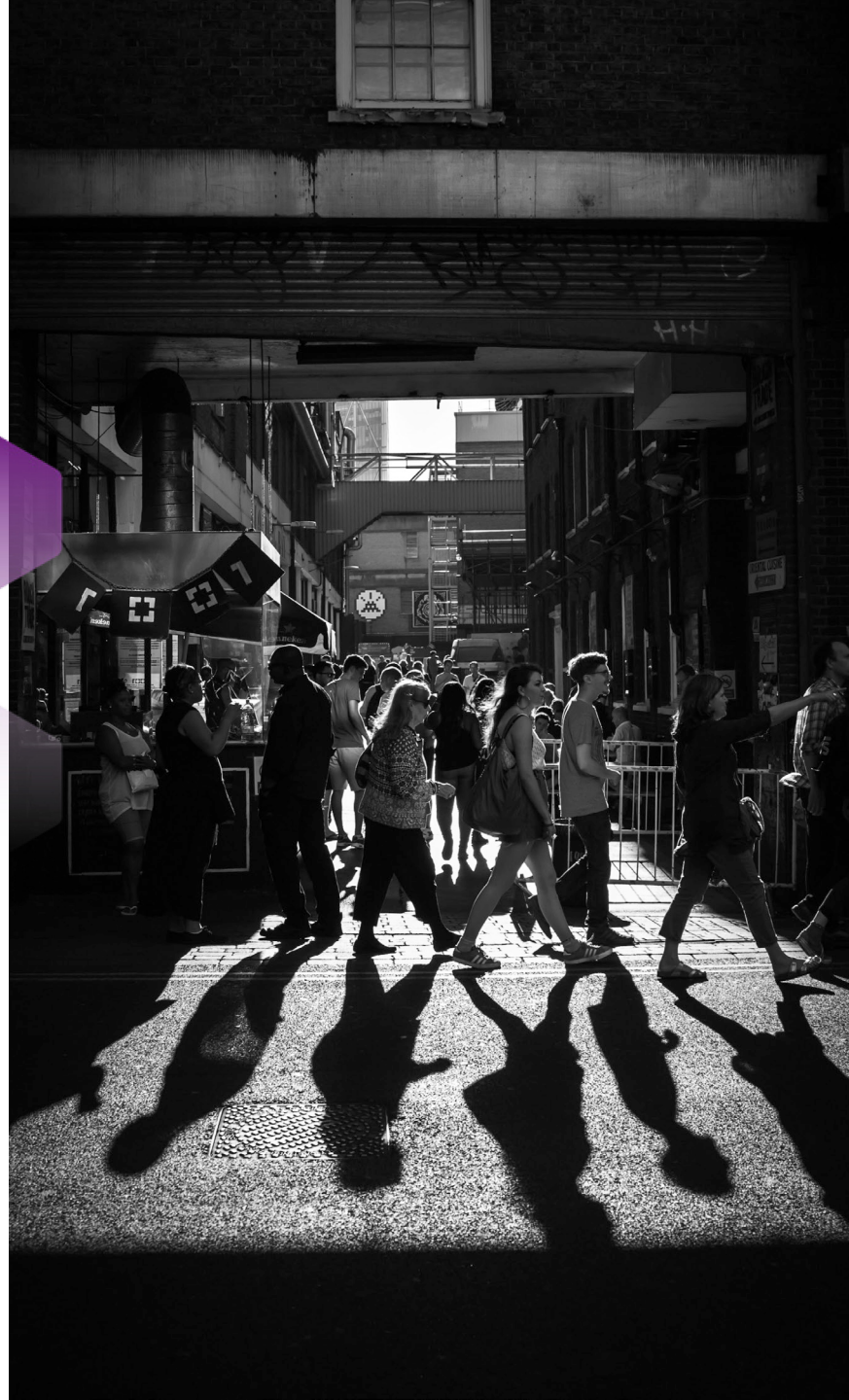
UKRI Economic and Social Research Council



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Machine Learning for Privacy Metadata Annotations

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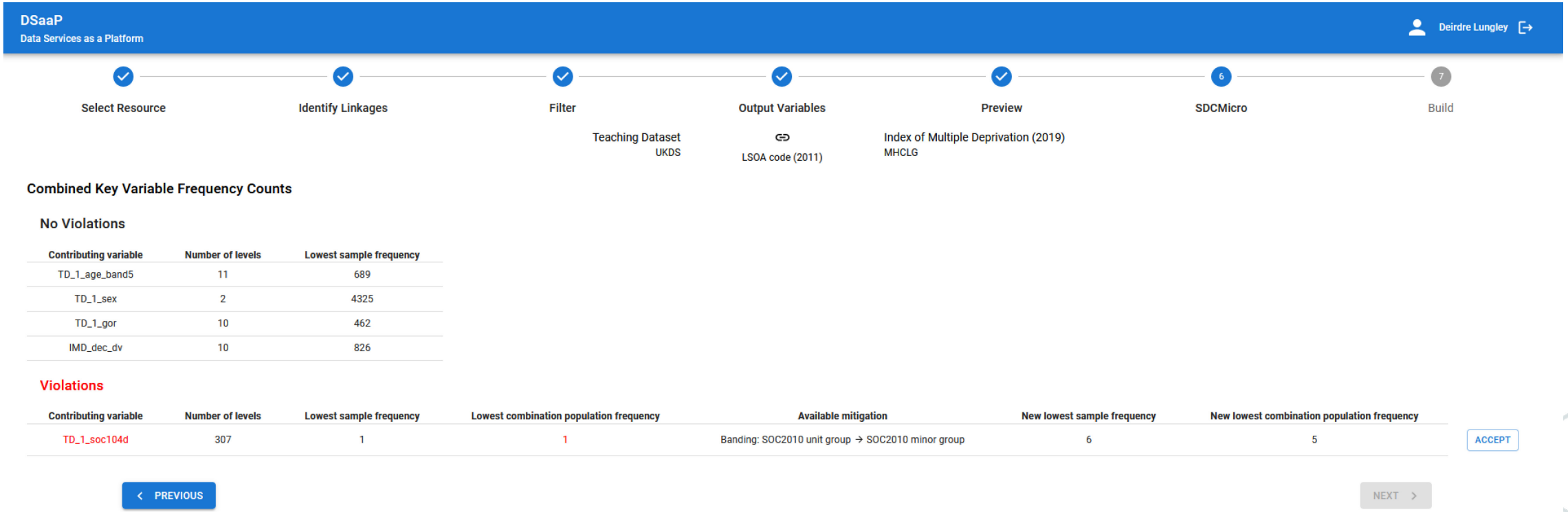
Goal: Automated Disclosure Risk Analysis (DRA)



Automated DRA Dependencies

- Identify key (potentially disclosive) variables.
- Fast computation of combination frequencies of these key variables.
- Stored population frequencies for these key variable combinations.
- Hierarchical conceptual ontology structures.

Improved Computational Performance

	A	B	C
0	22	77	44
1	33	77	66
2	22	77	-9
3	22	77	55
4	33	77	44
5	33	77	44
6	11	88	-9
7	22	-9	44

Our approach computes frequency counts using bitmasks* (strings of 1s and 0s) that are then combined for each row

We achieve a > 30x performance improvement** versus R[1]

Steps

1. Compute bitmasks for each key variable
2. Compute fk[2] for each row in the data frame

Note: -9 is treated as NaN (wildcard) and matches any value

* Bitmask operations are very simple and therefore very fast.
  Main code is written in Python with bitmask manipulation in C++

** Best performance is achieved if only fk is calculated, not Fk (using weights)

References:

1. Templ, Matthias. (2008). Statistical Disclosure Control for Microdata Using the R-Package sdcMicro. Transactions on Data Privacy. 1. 67-85.

2. Franconi, Luisa & Polettini, Silvia. (2004). Individual Risk Estimation in μ-Argus: A Review. 3050. 262-272. 10.1007/978-3-540-25955-8_20.

Improved Computational Performance (cont.)

	A	B	C	fk
0	22	77	44	**3**
1	33	77	66	**1**
2	22	77	-9	**4**
3	22	77	55	**2**
4	33	77	44	**2**
5	33	77	44	**2**
6	11	88	-9	**1**
7	22	-9	44	**3**

Tested with the Quarterly Labour Force Survey
~96,000 rows

10 key variables

2-, 3- and 4-way combinations = 375 permutations
36 million rows in total

~5s to compute the bitmasks*

~15s to compute the fk frequency counts for all combinations*
~240s to compute weighted Fk as well

* Intel core i7-12700H, 32 GB

Friday 2nd June, Session 3, Powerful DDI-CDI Metadata – the How and the Why?, Tom Gilders, Darren Bell

Previous Automated Variable Annotation at the UK Data Archive

June 2012 - March 2013: SKOS-HASSET project (UKDS)

- Incorporated the use of the HASSET thesaurus to automatically index a wide range of the survey data resources of the UKDS.

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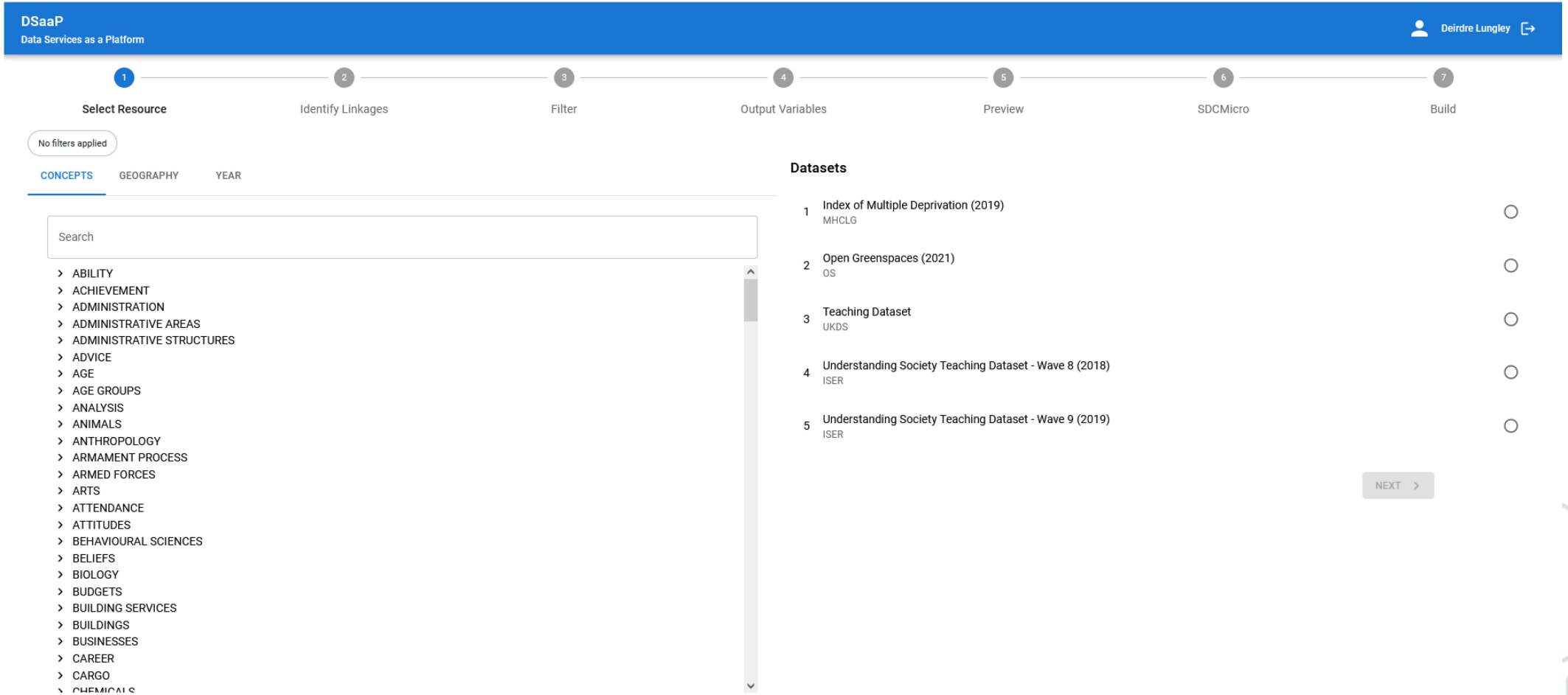
ML Variable Annotation objectives:

- Semantic tagging for resource discovery.
- Identify key variables (potentially disclosive) for our Disclosure Risk Analysis (DRA).

Semantic tagging for resource discovery



Identify key variables for DRA

- Key variables – potentially disclosive?
- Indirect identifiers can be any attributes or, more likely, combination of attributes that, are likely to be unique for at least some individuals in your dataset *and* in the population (UK Anonymisation Framework*).
- UKAnon example: A 16 year old widower living in rural Scotland.
- Disclosure Scenarios:
  - Nosy neighbour: an unsophisticated intruder who was trying to find a single specific individual.
  - Fishing attack (not phishing): finding unusual looking records in the dataset and attempting to find the corresponding individuals*.
- Key variable (demographic and socio-economic) public matching sources:
  - E.g. Electoral registers, land registry, estate agent listings.
  - Social media postings.
- Examples of key variables:
  - Address, age, sex, marital status, number of dependent children.

* Elliot, M., Mackey, E., & O'Hara, K. (2020). The Anonymisation Decision Making Framework: European Practitioners' Guide (2nd edition). UK Anonymisation Network. https://msrbcel.files.wordpress.com/2020/11/adf-2nd-edition-1.pdf

Context of our current ML variable annotation project: bounding the problem

- Objective – identify key variables. Initial subset:
  - Geographic (NUTS 3 to LSOA)
  - Sex
  - Age
  - Marital and civil partnership status
  - Household composition
  - SOC (1,2,3 and 4-digit codes)
  - SIC (1,2,3,4 and 5-digit codes)
  - Socio-economic Classification (NS-SeC)
  - Economic activity
  - Ethnic group
  - Country of birth
  - Language (main)
  - Religion
  - Highest qualification
  - Long term health problem or disability.
- Scope - Gold Standard Datasets.

Methodology:

- Apply model at variable group level, e.g. occupations:
  - UKDS gold standard datasets currently manually tagged with variable groups.
- Input features:
  - variable name
  - variable label
  - question text
  - variable group and subgroup.
- Multiple methods:
  - FastAI: language model based.
  - SVM: Support vector machines.
  - KNN: K-nearest neighbour.
- Multiple models:
  - Multi-class: Key variable related concepts.
  - Binary: Sensitive/Non-sensitive.
- Initially tune on one series – QLFS.
- Extend to other Gold Standard Datasets.
- Active learning – continually refining model.

Example Training Data: QLFS SOC Variable Group

	A	B	C	D	E
1	text	labels			
2	INDS07M Industry section in main job (1 charac) Standard Occupational Classification Main Job Industry	OCCUPATIONS|SIC2007|SECTION			
3	INDS07S Industry section in sec job (1 charac) Standard Occupational Classification Industry Occupation Second Job	OCCUPATIONS|SIC2007|SECTION			
4	INDD07M Industry division in main job (2 digits) Standard Occupational Classification Main Job Industry	OCCUPATIONS|SIC2007|DIVISION			
5	INDD07S Industry division in sec job (2 digits) Standard Occupational Classification Industry Occupation Second Job	OCCUPATIONS|SIC2007|DIVISION			
6	INDG07M Industry group in main job (3 digits) Standard Occupational Classification Main Job Industry	OCCUPATIONS|SIC2007|GROUP			
7	INDG07S Industry group in second job (3 digits) Standard Occupational Classification Industry Occupation Second Job	OCCUPATIONS|SIC2007|GROUP			
8	SC10MMJ SOC2010 Main Job Major Group Standard Occupational Classification	OCCUPATIONS|SOC2010|MAJORGROUP			
9	SC10SMJ SOC2010 Second Job Major Group Standard Occupational Classification	OCCUPATIONS|SOC2010|MAJORGROUP			
10	SC10MMN SOC2010 Main Job Minor Group Standard Occupational Classification	OCCUPATIONS|SOC2010|MINORGROUP			
11	SC10SMN SOC2010 Second Job Minor Group Standard Occupational Classification	OCCUPATIONS|SOC2010|MINORGROUP			

Current progress

- Currently covered key variable groups:
  - Standard Occupational Classification, e.g., SOC, SIC, NS-SEC, economic activity.
  - Respondent and household characteristics, e.g. sex, age, marital status.
  - Ethnicity, country of birth, language, religion.
- Consistent high accuracy within QLFS series as expected.
- Generalisation methodology:
  - Iteratively folding in additional gold standard datasets:
    - Binary classifier to identify variables for variable group, e.g. occupations.
    - Testing, updating training data, retesting.

Any questions?

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Thank you.

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