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LUND UNIVERSITY

AI-education @ Lund University
Report #2

LUND UNIVERSITY

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Executive summary

This is the second of three planned reports about AI education at Lund University. It provides updated data about Lund University courses and staff with self-assessed AI knowledge; provides comparison data with a number of other Swedish higher education providers; discusses the related data situation at Lund University; and outlines the roadmap for the third and final leg of the project.

The project ambitions – a recap

The project runs through 2021, and this is the second report out of the three we have planned. Overarching ambitions and results so far are discussed.

AI teaching capacity – an update

The list of teachers with AI-related competencies has been updated since report #1. The current list is presented and discussed, and we introduce a planned autumn expansion.

AI courses@LU – an update

The list of AI-related courses has been updated since report #1. The current set is presented and discussed. We also add sections about PhD courses, MOOCs and commissioned education efforts at LU.

Lund University and AI education in a comparative national context

We have compared LU's AI-related courses to offerings by a set of other national Universities. We discuss how this comparison was carried out technically, and present some results stemming from that exercise.

Looking inward: the data situation at Lund University

In report #1, we highlighted a number of technical deficiencies making necessary analysis of what we are up to as a university, and what capacity we can access in certain areas, unduly difficult. In this report, we dig deeper and suggest the outline of an "LU analytics" system that would make such internal analysis quicker, more effective and far less expensive. We also furnish a few further suggestion how the data situation can be improved.

Contents

1. Project ambitions and timeline – a brief recap

1.1 Operative project ambitions

In this project we have the following operative ambitions:

A. Fact-finding: fundamental questions

- *What* AI-related courses are LU offering on the undergraduate and master levels? *This has been expanded to include at least some courses on the PhD candidate level.*
- What *sort* of AI-related courses are being offered?
- *Where* are these courses hosted (faculty/cross-faculty)?
- How do LU's offerings *compare* to a range of national and international universities?
- What related *teaching capacity* does LU have access to?

B. Based on the processed information: furnish strategic suggestions/development ideas how to bolster/complement AI education at LU.

The project will come up with several concrete suggestions both of a long-term strategic kind, and of concrete on-the-ground measures. Such advice is only intended as input to the core Lund University leadership to aid future decision-making, and should not be construed as political statement what *should* be done.

C. Facilitating information exchange about AI education between different stakeholders (e.g., AI Lund, LUCE, RL, Faculties)

LU course and teacher data in the project can be made useful as soon as it is collected as resources and needs in the organisation can be better matched – provided the data is properly disseminated. An ambition is that the project should facilitate such matching efforts.

D. Representing LU in national and international fora where AI in education is a major focus

To put LU on the map as well as to better understand the larger educational context LU is situated in, an original ambition was for us to represent LU in a variety of national and international fora where AI in education was a core focus. The Corona situation has thrown such plans off kilter, however.

1.2 Overarching “end zone” ambition

The above operative ambitions all feed into a common overarching ambition: **to suggest and help set up university-wide AI-focused courses.**

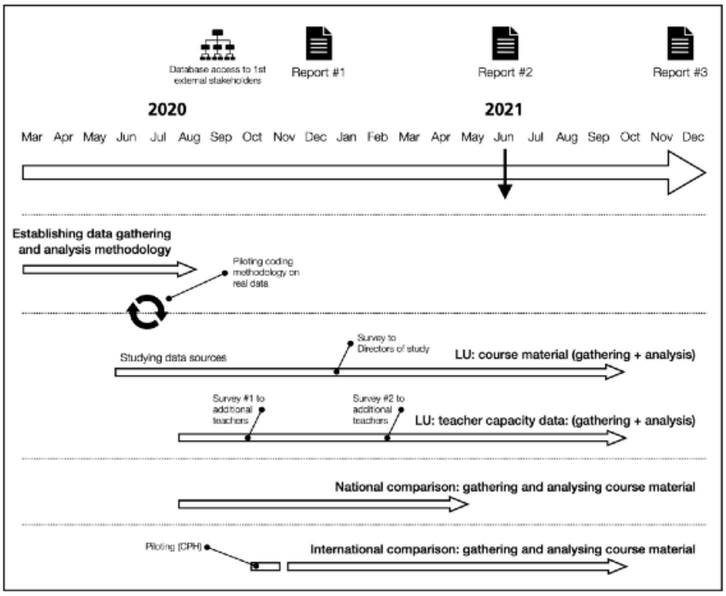
1.3 Project timeline and major deliverables

The project was initially slated to start on February 1, 2020, but was delayed for a further month, and went live in March. It is intended to finish on December 31, 2021. We are roughly aligned with initial timeline planning, and have in fact been able to expand our objectives slightly in that we take an early look at PhD courses in addition to the originally planned first and second cycle courses.

The project will produce three core reports (of which this is the second), and an infrastructure solution to aid collection, analysis and dissemination of data about LU courses and teacher capacity, and course data about a range of Swedish and international universities.

Beyond these hard milestones, we continuously link with the AIML/AI Lund group, LUCE, and present the project to other entities as requested.

Figure 1.1 Overarching project timeline



Report 1 – published in December 2020
Lund University AI-related courses and teaching capacity: a tentative analysis

Contents

- General analytical framework description
- *Course information*: description of methodology, opportunities, challenges; coding methodology + preliminary findings.
- Gathering *teaching capacity information*: description of methodology, opportunities, challenges; data gathering; coding methodology + preliminary findings.
- Description of the database/infrastructure, and how it can be used outside of the core project to aid information gathering and dissemination about AI-related resources at LU, including comments about LU data sources and how they can and could be used to aid similar comparison efforts.

Report 2 (this report) – June 2021
Updates and Lund University AI-related education in a national context (for details, see next chapter).

Report 3 – December 2021 (planned)
Lund University AI-related education including an international outlook

Contents

- Updates to LU data
- International data selection and analysis explained
- LU and AI education: an international comparison pilot
- LU AI teaching capacity now and in the future
- The project summed up: methodological challenges and how future efforts (including but not limited to AI-related ones) can be better and more systematically supported.
- The project summed up: *where can LU go from here?*
  - Capacity building
  - Focus
  - Inter-faculty efforts
  - Inter-university efforts
- Strategic ambitions? Organic growth? Aiming for excellence?
- The data situation at LU revisited

2. This report – ambitions

In this second report the main ambitions are:

- To present updated data about Lund University AI-related courses and teaching capacity. We will continue to gather more data even after this report, in order to be able to furnish a fully up-to-date presentation in the final report in December 2021.
- To introduce an expansion of those ambitions, *viz.* an early look at LU PhD courses, MOOCs, and commissioned education efforts where AI is a component.
- To present the two-pronged methodology we have developed to compare Lund University course offerings with equivalent offerings at a range of other Swedish (and eventually some international) universities.
- To describe aims and ambitions of that comparison effort, and explain why we have opted for the specified set of comparison cases.
- To present the actual comparison.
- To take a longer look at the data situation at Lund University, and present ideas how this can be improved to facilitate analyses of this kind.

3 AI courses @ Lund University – an update

3.1 Course data updates: an overview

In this chapter we update the list of found AI-related courses and discuss this data, which will then also be the data to be compared to other universities in the next chapter. The "trawling methodology" was explained in Report #1, but to aid new readers, we furnish a slightly abridged version of this explanation in Appendix 2.

After the completion of report #1 in December 2020, we sent out a survey to 86 directors of study. The respondents were asked gauge whether the courses we had already found appeared relevant from their perspective, and to suggest more courses that we might have overlooked.

We received 55 answers and used that information to revise the initially located list of courses. That response rate is not bad given the lack of a consistent data-gathering situation at the university that we will return to in chapter 6, and the general screen and survey fatigue in a Corona year. Questionnaires jacking in from the side, as it were, will after all never get the traction and priority that an officially condoned or even mandated information channel would.

We have additionally followed several bespoke leads in order to find courses that may not have been caught using the main trawling methodology.

Even so, we have not found a wealth of new courses, and the overarching analysis has for that reason not notably been affected by the additional cases. At this point we are including 50 courses as compared to 39 courses in report #1. The additional efforts to dig up more relevant data have the benefit that we are more confident than we were in report #1 that we have in fact caught a majority of AI-related courses at LU.

Better Lund data -> worse comparison data

We recognise that our multi-pronged data-gathering methodology will inevitably affect the later comparison effort, as it would be infeasible to replicate these various methods for each university. As we shall see in chapter 4, the case of Linköping University would seem to corroborate this concern.

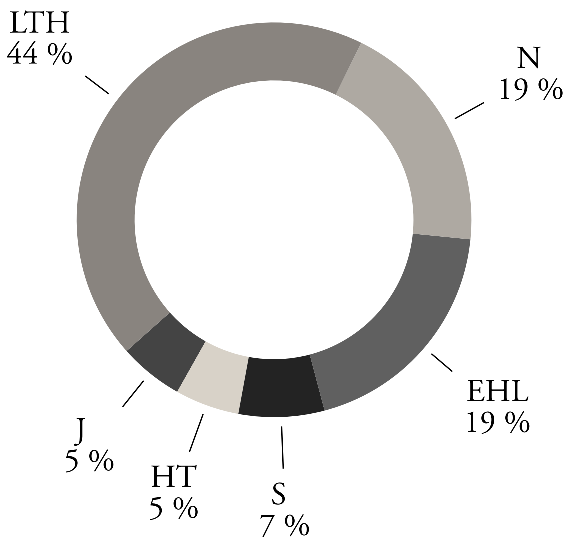
On the other hand, it means that a primary task, to map what LU is offering in terms of AI-related courses, is more faithfully and comprehensively executed.

3.2 Update – type of AI-related courses @ LU (aggregated data)

We first update and present aggregated course data to see where courses are housed, and what focus they have.

As before, the Faculty of Engineering (LTH) followed by the Faculty of Science (N) and the School of Economics and Management (EHL) provide most of the courses, see chart:

Diagram 3.1 Per cent of located AI-related courses (n=57) per faculty



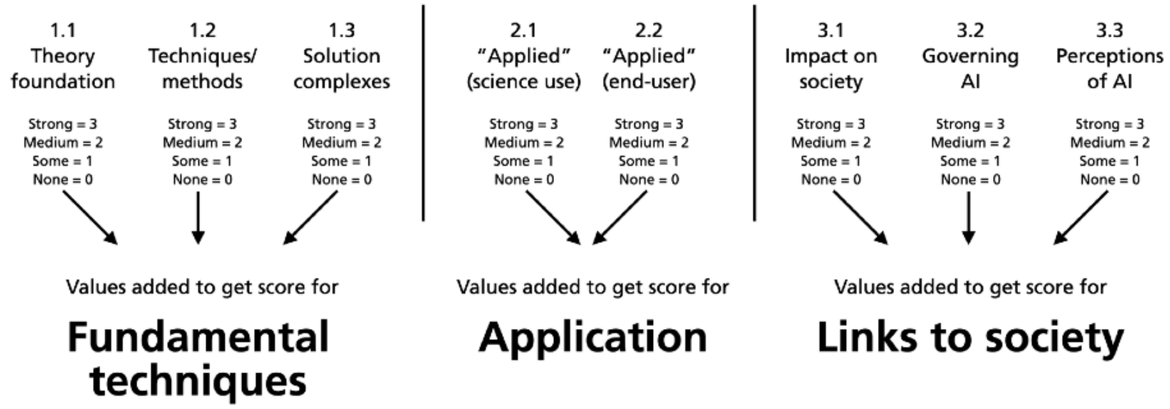
Nb. Seven of these courses overlap faculty boundaries, even though they have unique course codes, and are offered by two faculties. There are six overlaps between LTH and N, and one between HT and LTH. In the diagram, these courses are counted as if they were wholly separate, i.e., they are counted as individual LTH, N and HT courses. To avoid redundancies, these courses are counted as single instances elsewhere in this report, which explains why we use n=50 throughout the rest of the text when discussing Lund.

Two faculties are notable by their absence: M (Medicine) and K (Fine and Performing Arts).

In the case of M, this may be the result of organisational solutions where other faculties are brought in to furnish relevant courses (LTH seems to offer at least one M-related course) and/or that AI aspects are integrated in courses with (at least ostensibly) other overarching ambitions. For K, we would perhaps have expected any (or most) hits to pertain to category AI8 *AI perceptions,* but it should be said that that category is in fact rarely noted in the national comparison (see chapter 4).

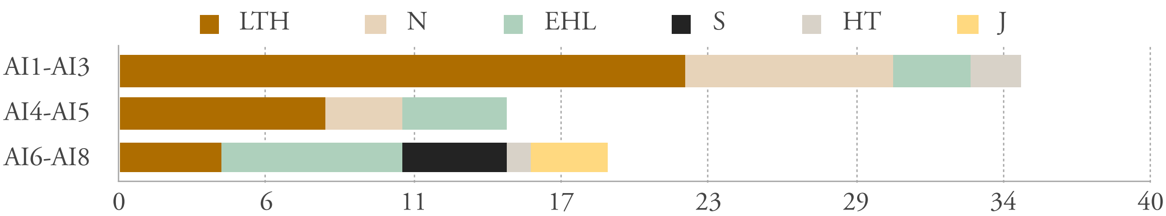
To determine AI *focus* for each course, we have employed our coding scheme (explained further in Appendix 1), where each sub-category can be coded as strong, medium, some or none, and then be aggregated to provide category "scores" for the three top-level categories *fundamental techniques, application,* and *links to society* (see figure 3.1, below).

Figure 3.1. From category self-assessment to assessment scores



In diagram 3.2, below, we see that one overarching category in the typology, *Fundamental techniques,* (AI1-AI3) dominates. As might perhaps be expected, LTH and N dominate not only *fundamental techniques*, but also *application* (AI4-AI5).

Diagram 3.2 Number of categorised "hits" per faculty 1

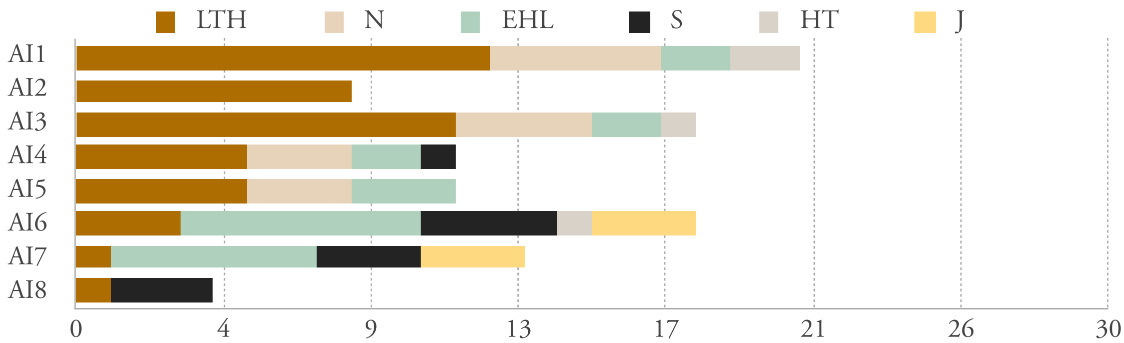


Nb. A single course can engender multiple categorisation "hits". We have not here taken into account whether the couplings are *strong*, *medium* or *some*. Any categorisation beyond "none" will register as a "hit".

AI1-AI3 = *Fundamental techniques* AI4-AI5 = *Application* AI6-AI8 = *Links to society*

Looking at course content per *sub*-category and faculty (diagram 3.3, below). The difference between diagrams 3.2 and 3.3 is not only cosmetic: it shows how we gather and code data in a way that allows us an option to decide how deep we want to "drill". Had we only opted to gather couplings to the overarching three categories (*fundamental techniques*, *application* and *links to society*), it would be impossible at a later stage to delve deeper than that.

Diagram 3.3 Number of categorised "hits" per faculty 2



Nb. A single course can engender multiple categorisation "hits". We have not here taken into account whether the couplings are *strong*, *medium* or *weak* (any categorisation beyond "none" will register as a hit).

AI1 = Theory foundation
AI2 = Techniques/methods
AI3 = Solution complexes

AI4 = "Applied" (sciences)
AI5 = "Applied" (end-user)

AI6 = Impact on society
AI7 = Governing AI
AI8 = AI perceptions

The *level* at which these course are being taught is also interesting. In diagram 3.4 (below) we also include PhD courses that will be discussed further in section 3.6.

We think the modest proportion of bachelor-level courses striking (if understandable), and suggest that this might be a strategic development area worth exploring further. A caveat is that long education programmes, such as in engineering, the distinction between bachelor-level courses and master-level courses is less relevant as the levels are more closely linked in these cases.

We went ahead and did a quick search for bachelor-level programmes with a distinct AI focus (using the search terms AI, artificiell, artificial, machine learning, maskininlärning, big data, image [to catch "image analysis" and related terms]). Excluding the full 300 credit Master of Science in Engineering programmes (which of course include bachelor-level elements), we recorded 10 hits – all 180 credit programmes. Of these, 8 had generic titles, but AI was evidently included in the searchable texts, while two had titles that indicated an explicit AI-related focus: Kandidatprogram i tillämpad AI (Mälardalen University College) and Maskiningenjör – Automation och AI (Borås).

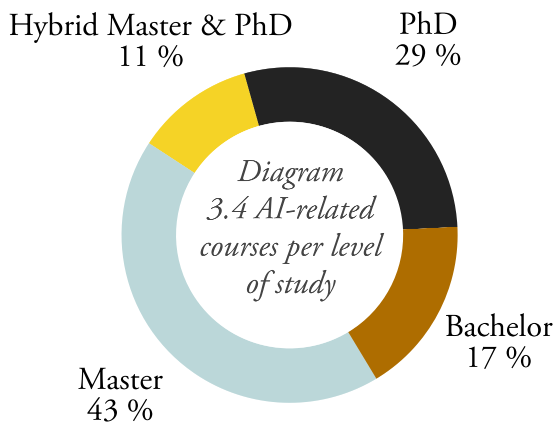
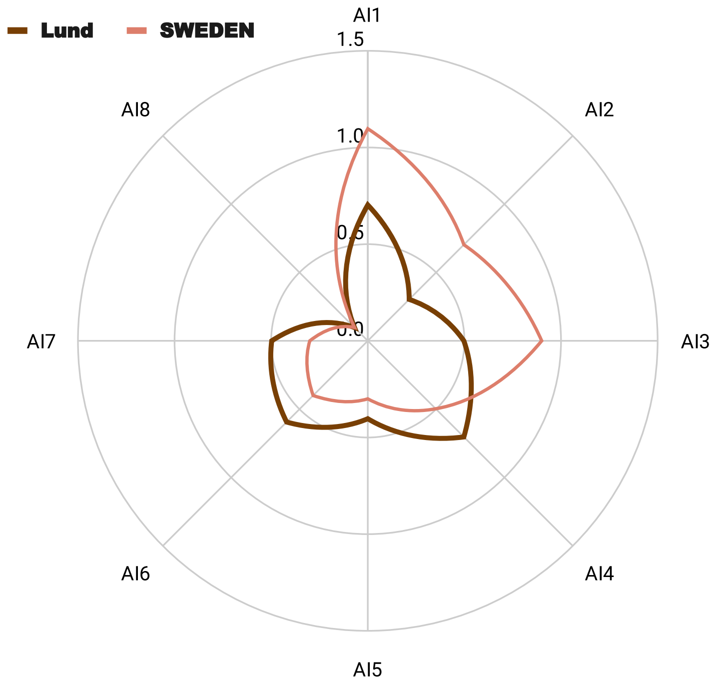


Diagram 3.4 AI-related courses per level of study

3.3 New: "fingerprinting" course type foci

To facilitate the coming comparison effort (next chapter), we also provide a radar chart of the average coding scores for each subcategory, see diagram 3.5, below.

Diagram 3.5 Average of coded values for each category



For each category: Strong = 3; Medium = 2; Some = 1; None = 0.

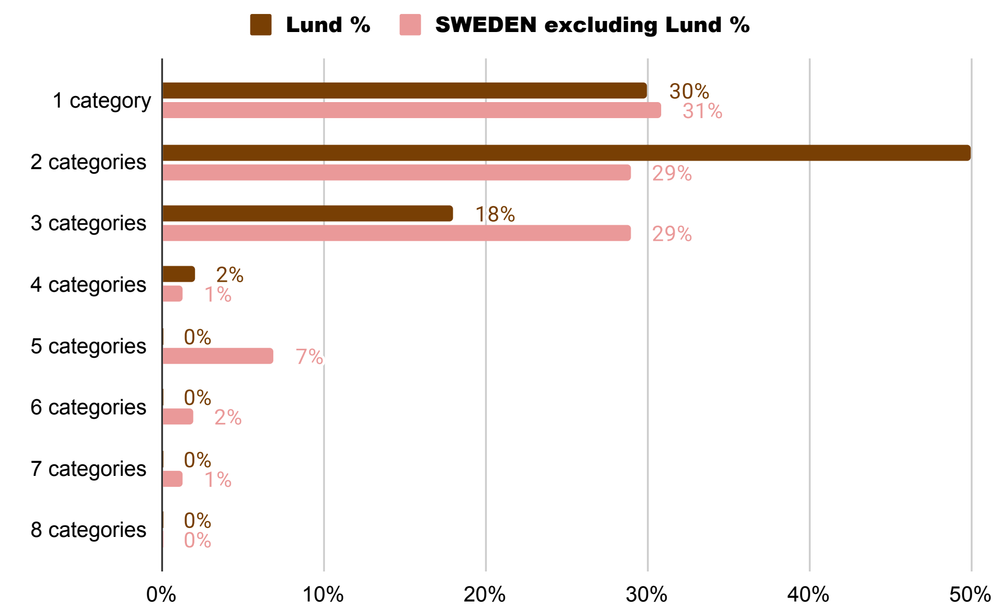
(Lund: n=50; Sweden: n=209)

In this figure we demonstrate how the resulting Lund AI-focus "fingerprint" can be compared with other data sets, in this case the aggregate national one (*including* Lund in this case – later in the chapter Lund will be compared with the Swedish universities *excluding* Lund). This will constitute a recurring component in the university-by-university comparisons in chapter 4.

3.4 New: cross-cutting courses

With (we hope) most of the Lund University AI-related courses in place in our database, we also wanted to look at the extent to which they "cross-cut" our eight analytical categories. To somehow link the various aspects of AI, from under-the-hood technical foundations all the way to how it is perceived and talked about in society would seem essential. This is also a metric that can be, and will be, used in the national comparison. In the following diagram (diagram 3.6, below), we demonstrate such a comparison as Lund is compared to national aggregated data.

Diagram 3.6 AI category spread (per cent of assessed courses)



Lund: n = 50; Sweden: n=xx

Categories:

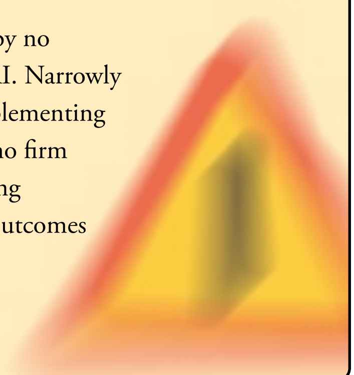
AI1 = Theory foundation	AI4 = "Applied" (sciences)	AI6 = Impact on society
AI2 = Techniques/methods	AI5 = "Applied" (end-user)	AI7 = Governing AI
AI3 = Solution complexes		AI8 = AI perceptions

Any given course can potentially be "hitting" anything from a single analytical category to all eight. As we can see, Lundian courses never spread across more than three such categories, while wider spreads are in evidence elsewhere (see e.g., the Royal Institute of Technology – KTH – comparison in the next chapter).

A notable aspect is the apparent chasm between the *Links to Society* category group (sub-categories 6-8) and the more technically-oriented categories. Of all 50 coded LU courses, only four seem to bridge this divide at all.

A problem or a conscious design parameter?

To introduce links between the analytical categories *within* individual courses is by no means the only way to realise an ambition to provide a broad understanding of AI. Narrowly focused courses could link to equally narrowly focused courses introducing complementing perspectives, and do so in a consciously designed fashion. Our data can provide no firm answers whether this is the norm or not, but it is generally harder to plan "learning outcome pathways" that span multiple courses, than to make sure that learning outcomes are established, and then made realistic and real within the confines of individual courses. To at least highlight the need to make *conscious* design decision to "go wide" (or not) would appear to be a good start.



3.5 New: presentation of individual courses

In report #1, we for the most part focused on the aggregate level, and on showing the general distribution of courses across the university according to specified criteria. In this report we will also present tables including all Lund courses we have located thus far, sorted by a selection of criteria.

The three tables below (3.1 – 3.3) list courses by overarching classification category, and sorted by the estimated strength of each category (this was explained in section 3.2). The database, also a project deliverable (see Appendix 3) contains links to more information about each course, including syllabi and teaching teams, and provides plenty of options to search and manipulate course data.

Course missing in action? Let us know!

Our hope is that this will prove interesting in and of itself, but also that this can help us set up a final data-gathering effort: anyone reading this report before early November 2021 who thinks that a course is either misplaced or plain missing is encouraged to contact us so we can revise the final report accordingly.

Nb. Be aware that we have thus far limited searches to the 2020/21 timeframe, but aim to complement with new additions in report 3, so keep the suggestions coming!

We have gathered all included courses for all case universities in Appendix 4. Reading through the list of course names will give a separate perspective when considering what Lund offers vis-à-vis what other institutions offer. Gaming AI architecture, eHealth, social media AI, smart cities, and sports analysis are examples of course foci which do not seem to have immediately recognisable Lundian equivalents (although such elements might surely be included in course with other headings).

Table 3.1 – Fundamental techniques

Code	Course name	Level	Credits	Faculty
Course focus coded as STRONG				
(aggregate coded score > 5 and/or at least one subcategory assessed as "strong")				
EDAP01	Artificiell intelligens	Master	7,5	LTH
MATC20	Bildanalys	Master	7,5	LTH+N
FMAN95	Datorseende	Master and PhD	7,5	LTH
FRTF25	Introduction to Machine Learning, Systems and Control	Bachelor	7,5	LTH
FYTN14	Introduktion till artificiella neuronnätverk och deep learning	Master	7,5	LTH+N
FMAN45	Maskininlärning	Master and PhD	7,5	LTH
FMAN30	Medicinsk bildanalys	Master and PhD	7,5	LTH
EITP25	Minnesteknologi för maskininlärning	Master and PhD	7,5	LTH
FRTN65	Modelling and Learning From Data	Master	7,5	LTH
FRTN50	Optimering för maskininlärning	Master	7,5	LTH
MASM25	Spatial statistik med bildanalys	Master and PhD	7,5	LTH+N
EDAN95	Tillämpad maskininlärning	Master and PhD	7,5	LTH
Course focus coded as MEDIUM				
(aggregate assessment score = 4 or 5)				
BMEF20	Neuroteknik	Bachelor	7,5	LTH
FRTN70	Projekt i system, reglering och maskininlärning	Master	7,5	LTH
EDAN20	Språkteknologi	Master and PhD	7,5	LTH
STAN47	Statistik: Deep learning och metoder för artificiell intelligens	Master	7,5	EHL
Course focus coded as SOME				
(aggregate assessment score = 1, 2 or 3)				
STAE02	Bayesian Methods	Bachelor	7,5	EHL
BINP16	Bioinformatik: Programmering i Python	Master	7,5	N
KOGP05	Kognitionsvetenskap: Neuromodellering, kognitiv robotik och agenter	Master	7,5	LTH+HT
KOGP09	Kognitionsvetenskap: Teorier och modeller i kognitionsvetenskap	Master	7,5	HT
MASM22	Matematisk statistik: Linjär och logistisk regression	Master	7,5	LTH+N
MASM17	Matematisk statistik: tidsserieanalys	Master	7,5	LTH+N
MASM11	Monte Carlo and Empirical Methods for Stochastic Inference	Master	7,5	LTH+N
BMEF20	Neuroteknik	Bachelor	7,5	LTH
MASM27	Nonparametric Inference	Master	7,5	N
EITN90	Radar och fjärranalys	Master	7,5	LTH
TNSN01	Servicerobotik	Master	7,5	LTH
STAE03	Statistik: Affärsanalys	Bachelor	7,5	EHL
FRTF20	Tillämpad robotteknik	Bachelor	7,5	LTH

Table 3.2 – Application

Code	Course name	Level	Credits	Faculty
Course focus coded as STRONG				
(aggregate coded score > 5 and/or at least one subcategory assessed as "strong")				
BINP11	Bioinformatik: Bioinformatik och sekvensanalys	Master	7,5	N
BIOS13	Biologi: Modellering av biologiska system	Master	7,5	N
EDAP20	Intelligent Autonomous Systems	Master	7,5	LTH
FMAN30	Medicinsk bildanalys	Hybrid Master and PhD	7,5	LTH
STAN45	Statistics: Data Mining and Visualization	Master	7,5	EHL
STAN47	Statistik: Deep learning och metoder för artificiell intelligens	Master	7,5	EHL
KOMC30	Strategisk kommunikation: AI, kognition och kultur	Bachelor	15	S
Course focus coded as MEDIUM				
(aggregate assessment score = 4 or 5)				
	None coded as such			
Course focus coded as SOME				
(aggregate assessment score = 1, 2 or 3)				
FMAN95	Datorseende	Hybrid Master and PhD	7,5	LTH
NEKN92	Finans: Finansiell ekonometri	Master	7,5	EHL
FMAF35	Linjär och kombinatorisk optimering	Hybrid Master and PhD	6	LTH
FMAN45	Maskininlärning	Hybrid Master and PhD	7,5	LTH
FRTN70	Projekt i system, reglering och maskininlärning	Master	7,5	LTH
NGEN08	Satellitbaserad fjärranalys	Master	15	N
TNSN01	Servicerobotik	Master	7,5	LTH
STAE03	Statistik: Affärsanalys	Bachelor	7,5	EHL
FRTF20	Tillämpad robotteknik	Bachelor	7,5	LTH

Codings/types are not discrete

Please note that a course can generate "hits" in more than one of the three tables if its focus is not strictly limited to one of the three overarching categories *fundamental techniques, application* or *links to society*.

Table 3.3 – Links to Society

Code	Course name	Level	Credits	Faculty
Course focus coded as STRONG (aggregate coded score > 5 and/or at least one subcategory assessed as "strong")				
SIMS40	AI i samhället	Master	15	S
VFTN75	Den smarta stadens styrning: AI och etik i en spatial kontext	Master	7,5	LTH
INFA40	Digitalisering och AI ur ett organisations- och samhällsperspektiv	Bachelor	7,5	EHL
HARA30	Handelsrätt: Rättsliga aspekter på artificiell intelligens	Bachelor	7,5	EHL
HARA35	Juridik och Artificiell Intelligens (AI)	Bachelor	7,5	EHL
INFN65	Verksamhet och artificiell intelligens	Master	7,5	EHL
Course focus coded as MEDIUM (aggregate assessment score = 4 or 5)				
JUDN23	Beskattning i den digitala eran	Master	15	J
HARG25	Europeisk dataskydssrätt	Bachelor	15	EHL
JAEN61	Europeisk patenträtt	Master	15	J
HARN52	Immaterialrätt, digitalisering och artificiell intelligens	Master	7,5	EHL
JUCN32	Medicinsk rätt	Master	15	J
SKOB31	Strategisk kommunikation och digitala media	Bachelor	7,5	S
SKOP21	Strategisk kommunikation: Public Relations	Master	7,5	S
Course focus coded as SOME (aggregate assessment score = 1, 2 or 3)				
EDAP01	Artificiell intelligens	Master	7,5	LTH
DIKA11	Digitala kulturer: Teorier - Introduktion	Bachelor	7,5	HT
NEKN92	Finans: Finansiell ekonometri	Master	7,5	EHL
EDAP20	Intelligent Autonomous Systems	Master	7,5	LTH
BMEF20	Neuroteknik	Bachelor	7,5	LTH
KOMC30	Strategisk kommunikation: AI, kognition och kultur	Bachelor	15	S

3.6 PhD courses

The reception of report #1 made it clear that many stakeholders wanted complementing information about AI-related PhD courses, arguing, quite sensibly, that such courses may come about much quicker, and are also usually more closely interlinked with ongoing research – in short, the that any list would be woefully incomplete without this addition.

While this task was not included in our original project brief, we recognise such arguments as valid, and have started to devote some time to find and code this material, and present a table (table 3.4, below) of initially located courses below (for now we gather all such courses in a single table that includes course identifiers, faculty "homes", credits, and coding scores). We will at this point provide limited commentary, but hope to be able to return to this issue in report #3.

A relaxed course gathering methodology

As we have (so far) no ambition to compare PhD course data to other universities' offerings, we have relaxed the restriction to code and present only 2020/2021 courses, and a few of the included PhD courses are for that reason outside this primary timing window.

With the qualification that data sourcing looks problematic (see *data quality caveats* box below), and that we have just started this work relating to this level of studies, the heavy focus of PhD courses to a single faculty, and one of our coded types *(fundamental techniques)* is eye-catching. At this point of AI debate, development and implementation, we would intuitively have expected a broader range of PhD courses. *We would suggest a special investigation into the potentially missed opportunities in this respect.*

Data quality caveats

If the data situation relating to first and second cycle courses at LU is challenging, for PhD courses it is more problematic still. As far as we can tell, there is *no common data source at LU where detailed information about all PhD-level courses is stored.* Courses that are established and run locally may be highly ephemeral in nature, and detailed knowledge about them may, it seems, very well be limited to that particular unit. Course titles and credits can be found in LADOK, and LTH has developed a more systematic approach which may potentially be an inspiration going forward.

Nb. The lack of administrative overhead is in part a strength, as departments can speedily and with a minimum of fuss muster and apply resources to educate their PhD candidates. But it nevertheless also makes for a scattered data situation if and when LU wishes to accumulate and analyse information about an important education component.We will return to this when we discuss the data situation in chapter 6.

Missing a course in the list? Let us know!

Given the data situation, we are extra eager to gather more information about relevant PhD courses. If you realise that a course is missing from the table, or that a course is misplaced, please let us know, and we will revise the list in the final project report.

Table 3.4 – AI-related PhD courses

Code	Course name	Pure PhD or hybrid	Credits	Faculty	Funda-mental techniques	Appli-cation	Links to society
EDA070F	AI och samhälle: juridiska, etiska och samhällsrelaterade aspekter av AI	PhD	3	LTH	Some	-	Medium
–	Artificial Intelligence in Medicine and Life Sciences – AI for Image and Video Data	PhD	1,5 or 6	M	Some	Some	Some
NTF005F	Artificial Neural Networks and Deep Learning	PhD	7,5	N	Strong	-	-
NTF012F	Artificiell intelligens inom medicin och livsvetenskap	PhD	1,5	N	Some	Strong	Some
FRT165F	Autonoma system	PhD	12	LTH	Strong	-	-
FRT195F	Autonoma system del 1	PhD	6	LTH	Strong	-	-
FRT200F	Autonoma system del 2	PhD	6	LTH	Strong	-	-
FMA171F	Bildanalys	PhD	7,5	LTH	Strong	-	-
FMA105F	Bildanalys för doktorander	PhD	7,5	LTH	Strong	-	-
FMA271F	Datorseende	Hybrid	7,5	LTH	Strong	Some	-
FRT220F	Deep Learning och GANs	PhD	6	LTH	Strong	-	-
MAM040F	Digi MTOS - Det digitala mötet mellan människa, teknik, organisation och samhälle	PhD	7,5	LTH	-	-	Some
EDA055F	Grafiska modeller, Bayesiansk inlärning och statistisk sambandsbaserad inlärning	PhD	6	LTH	Strong	-	-
EDA065F	Inlärningsteori och förstärkningsinlärning	PhD	6	LTH	Some	-	-
NTF006F	Introduktion till deep learning	PhD	4,5	N	Medium	-	-
EIT155F	Introduktion till maskininlärning	PhD	7,5	LTH	Some	-	-
FMAF35F	Linjär och kombinatorisk optimering	Hybrid	6	LTH	-	Some	-
FMAN45F	Maskininlärning	Hybrid	7,5	LTH	Strong	Some	-
FMA085F	Maskininlärning	PhD	5	LTH	Strong	-	-
EIT195F	Maskininlärning	PhD	7,5	LTH	Strong	-	-
FMAN30F	Medicinsk bildanalys	Hybrid	7,5	LTH	Strong	Strong	-
EITP25F	Minnesteknologi för maskininlärning	Hybrid	7,5	LTH	Strong	-	-
FMAN60F	Optimering	Hybrid	6	LTH	Some	-	-
EDA025F	Programmeringsmodeller och metoder för att hantera stora datamängder	PhD	7,5	LTH	Strong	-	-
FRT190F	Projekt i autonoma system	PhD	6	LTH	Some	-	-
FRT160F	Realtids- och inbyggda system med tillämpningar mot maskininlärning	PhD	5	LTH	Strong	-	-
FMSN20F	Spatial statistik med bildanalys	Hybrid	7,5	LTH	Strong	-	-
EDAN20F	Språkteknologi	Hybrid	7,5	LTH	Medium	-	-
FRT170F	Studiecirkel i djupa neuralnät	PhD	7,5	LTH	Some	-	-
FRT240F	Studiecirkel om Deep Reinforcement Learning	PhD	5	LTH	Medium	-	-
EDAF70F	Tillämpad artificiell intelligens	Hybrid	7,5	LTH	Some	-	-
EDAN95F	Tillämpad maskininlärning	Hybrid	7,5	LTH	Strong	-	-
FRT245F	Tillämpad maskininlärning	PhD	3	LTH	Strong	-	-
FRT230F	Tillämpad maskininlärning I	PhD	4	LTH	Medium	-	-
FRT250F	Tillämpad maskininlärning III	PhD	3	LTH	Strong	-	-

By "hybrid" we mean courses that appear to be offered both for PhD candidates and master level students (the courses then usually have different course codes for the two levels, but we only present the PhD code in the table).

3.7 MOOCs and commissioned education

Lund University further organises a set of re- and upskilling opportunities for professionals, including *Massive Open Online Courses* (MOOCs), in the field of AI. In the interest of complete information, we asked our colleague Karima Kandi, analyst and area coordinator for AI at Lund University Commissioned Education (LUCE), to briefly discuss these:

Hi from Lund University Commissioned Education (LUCE)!

Commissioned Education in AI

While organisations and professionals face increasing demand to accelerate the adoption of artificial intelligence (AI), the need for re- and upskilling opportunities in AI has grown quickly in recent years. Furthermore, and as education continues to play a seminal role in organisations and professionals approach to AI, offering the right re- and upskilling opportunities for professionals can become a critical component in the toolbox organisations have access to when paving the way for the AI-driven digital transformation occurring today. In line with such trends, LUCE initiated a dedicate area for AI, in 2018, with the aim of taking a more comprehensive approach to AI professional re- and upskilling provision, together with faculties across the university.

Adding to these efforts, the department also expanded the systematic analysis and study of re- and upskilling needs as expressed by professionals and key market stakeholders. As part of a brief account from this ongoing work, trends, as detected by LUCE, continue to confirm that the need for educational content for professionals in Fundamental Techniques and Application (primarily user driven) will likely continue to expand. Upon deeper review, educational content that can meet the continuously accelerating need for introductory level and applied knowledge in AI appear especially crucial for professional in these areas. To add to these trends, interests in the fundamental techniques and applications of AI are increasingly also found accompanied by additional need to combine such knowledge with elements of other disciplines e.g. taken from social sciences, the humanities, law, economics, life sciences and more. As such, the number of calls for interdisciplinary courses in AI are expected to continue to rise as well.

This is a summary of LUCEs current portfolio of AI courses for professional:

Course	Course type	Faculty affiliation
Introduction to Applied Machine Learning	Blended learning: Online course with workshops	Faculty of Engineering
What is AI?	(info pending)	Faculty of Engineering, Faculty of Law, eSSENCE & Department of Computer Science
AI for Tech Managers	One day course and workshop	Faculty of Engineering in collaboration with ESS
AI in Society	Online and Workshops	Department of Arts and Cultural Sciences
Image Analysis	PhD course made available to professional education.	Faculty of Engineering
Artificial intelligence (AI) – something for our company?	Online course, 2 days	School of Economics and Management (Department of informatics)

Hi from Lund University Commissioned Education (LUCE)! (cont'd)

MOOCs

The term *Massive Open Online Courses* (MOOCs) refers to openly accessible online courses that are designed to fit a diverse group of learners and provide education *en masse*, wherein any expected learner with internet access can participate at any time, place and at a pace of their choosing – as well as predominantly free of charge. Together with *Coursera*, one of the leading online educational platforms in the world, Lund University currently offers a number of MOOCs for the fast growing 77+ million learners on the platform, along with globally leading universities as well as industry educational providers (e.g. Imperial College of London, Stanford, Yale, Science Po, IBM, Microsoft and more).

MOOCs are a fast-growing educational concept at Lund University, and correspondingly so in the portfolio of commissioned education. Following the successes of and expertise acquired from already published MOOCs, the concept was integrated into the area of AI at LUCE in late 2018. As part of this integration, a series of MOOCs were commissioned under the interdisciplinary theme of *Humans and AI* following a governmental call for universities to accelerate the development of introductory re- and upskilling opportunities in AI. As such, these MOOCs have been designed to combine introductory AI course content with elements of other disciplines, at present including: AI and the law, business and the future of work as well as ethics and societal challenges. Here is a summary of these MOOCs in LUCEs portfolio (which today also represents Lund Universities MOOCs in AI):

Course	Faculty affiliation	More information
AI & Law	Faculty of Law	www.coursera.org/learn/ai-law
AI, business and the future of work	*Centre for languages and Literature* Centre for European Studies	www.ai.lu.se/mooc (to be published in June 2021)
AI & societal challenges	Faculty of Social Sciences (Department of Political Science) and The Joint Faculties of Humanities and Theology (Department of philosophy)	www.ai.lu.se/mooc (to be published in June 2021)

For more information on AI MOOCs at LU, in relation to Alumni & Lifelong Learning, contact: Susanne Norrman, Department Manager at Lund University External Relations and member of steering board at AI Lund. For AI MOOCs at LUCE in relation to professional education, contact Karima Kandi.

4. LU/AI in a national comparison

In this chapter, the aim is to compare what Lund University offers in terms of AI-related courses to a selection of other Swedish universities. We will first explain the selection we have opted for and why, then carry out a two-pronged comparative analysis. Several caveats are in order: the field is quickly evolving, and the effort thus by definition stands on feet of clay. The main mitigation is that we will home in on what we consider to be some overarching *patterns*, and discuss some consequences and ideas based on this.

We will also delve somewhat deeper when we discuss Linköping University, as we have initiated a collaboration with Fredrik Heintz och Micael Frideros at that university (se more below).

4.1 Included Swedish universities and data

Realising that we would not have the resources to look at every Swedish tertiary education institution, we had to decide on a relevant sub-selection. Having considered feasibility parameters and stakeholder views, we ended up with the following list because they represent full-sized universities that can fruitfully be (and often are) compared with Lund (and/or the Faculty of Engineering, LTH): *Stockholm University, Uppsala University, University of Gothenburg*, and *Linköping University*. In addition, we included a a set of technically oriented institutions which we would expect are heavily invested in AI-related research and teaching: *Chalmers University of Technology* in Gothenburg, and the *KTH Royal Institute of Technology*.

To probe potential geographical similarities and/or complementing competencies, we also included *Malmö University* and (based on a lead) the much smaller *Swedish University of Agricultural Sciences*. Finally, and in order to follow another interesting lead, we have considered *Luleå University of Technology*.

The list can obviously and justly be challenged (any list could), and some highly interesting candidates have so far been left out. An expansion would for instance almost have to include Umeå University, as the *Wallenberg AI, Autonomous Systems and Software Program – Humanities and Society* (WASP-HS) is coordinated from there. We will see if we can find time and resources to include a comparison expansion in report #3.

The comparison includes Bachelor and master-level courses, but not PhD ones. As in the Lund-exclusive section (chapter 3), we have excluded project and exam courses where project/thesis work is the main focus, as many such courses are difficult to systematically locate and define as strictly AI-relevant even though individual projects may indeed be focusing on AI, and course syllabi are insufficiently detailed to allow proper coding according to our framework (they will inevitably be written in ways that allow a range of different theses/projects under the same syllabus aegis.

This is an accepted lacuna but nevertheless still a lacuna as the practical aspects of project work are an important educational complement that is, for now, being overlooked. This sense is reinforced by our Linköping friends who independently alerted us to this very fact. Together with the Linköping duo, we plan to take at least a first look at such material going forward.

To find AI-related courses at each seat of learning, we have used a modified keyword search – see more in Appendix 2.

4.2 Special collaboration: Linköping University

In the case of *Linköping University*, we first employed our default trawling methodology (keyword searches in existing/openly accessible databases). Then, after a propitious encounter with Fredrik Heintz that came about as a result of *AI Lund's* rich outreach activities, we gathered that Linköping was initiating an effort very much like our own. Heintz is the Director of the Graduate School for the Wallenberg AI Autonomous Systems and Software Program (WASP), President of the Swedish AI Society (SAIS) and a member of the European Commission High-Level Expert Group on AI.

Heintz and his wingman Micael Frideros proved willing to help us dig up a more complete set of AI-related courses, and we could in return code their courses using our developed framework which they adopted in their own investigation.

The important thing is that this endeavour yielded a list of LiU courses with twice the number of courses, and a humbling realisation that more courses are likely lurking beyond the reach of sweeping database searches in other universities too.

While this of course weakens any comparison results, we believe that AI as a prioritised national concern in education is in the end the main loser. If *we* cannot easily find all Swedish AI-related education opportunities, it begs the question how web-skimming prospective students will be able to find and assess them.

The Linköping collaboration also added some extra zest to the report as Messrs Heintz and Frideros proved willing to write a short text about this report and the employed methodology, and the utility such efforts could bring to external actors:

Hi from Linköping University!

On behalf of Linköping University, we would like to thank Mikael Sundström and Magnus Ekblad at Lund University for the opportunity to collaborate with them in this interesting and important project and for adding our comments to the report. The history of research and education in Computer Science and Artificial Intelligence at Linköping University is both long and broad. The Master of Science program in computer science and engineering (Civilingenjör Datateknik) has been given since 1975 and today the online course offering Elements of AI (Grunderna i AI) ranks as one of Sweden's most popular courses in Artificial Intelligence with more than 3000 students having passed the university course so far. Therefore, we regard ourselves as one of the leading universities in northern Europe within Artificial Intelligence, a view that is also reflected in data in this report.

LINKÖPING UNIVERSITY

Hi from Linköping University! (continued)

As partners in this project with Lund University we find the initiative both impressive and important, not only for the universities at Lund and Linköping but for all Swedish universities with research and education related to Artificial Intelligence. The initiative will support collaboration between universities as well as with external partners. It will also facilitate faster development through benchmarking between the different educational organizations leveraging best practices and experiences gained among the participating universities. In our view it is important that the work continues beyond these three reports at Lund University, preferably through a national effort.

As mentioned earlier in the report, one major finding is the difficulties in obtaining complete lists of AI-related courses through online databases. Therefore, it would be highly desirable if similar in-depth surveys as the one conducted at the universities in Lund and Linköping are done at all Swedish universities, so that the comparisons cross universities can be made on more equal terms.

Another aspect of the findings is the need for a more fine-grained classification of topics related to Artificial Intelligence based on a broad view on what these topics are, preferably by applying many different views from different universities and subject areas in order to reach consensus. In our view, this is especially important in an initiative for a national curriculum for a Master of Science program in Artificial Intelligence, and as a basis for strengthening the national progress in the AI-field.

That being said it is also important to be mindful about the complexity and the ever-changing nature of Artificial Intelligence. As the development in the AI-field progresses it is likely that new areas and new applications will emerge that changes the AI-landscape. Therefore, a dynamic, flexible and inclusive approach is needed for any organization that aspires to be relevant in Artificial Intelligence. This might be a struggle for universities since educational structures tend to have a lot of inertia, making it harder for them to be flexible and adjust to changes. Nevertheless, we argue that the universities are fundamental for Sweden's progress in the AI-field, to provide both cutting edge research and solid education for researchers, data scientists, data engineers, future corporate managers and basically anyone who needs to inform themselves about AI. This timely report is a great start towards this!

Fredrik Heintz
Associate Professor of Computer Science, Linköping University

Micael Frideros
Research Engineer AI, Linköping University

LINKÖPING UNIVERSITY

4.3 Footprint comparison

4.3.1 What do we mean by "footprint" and how can it be used in a comparison?

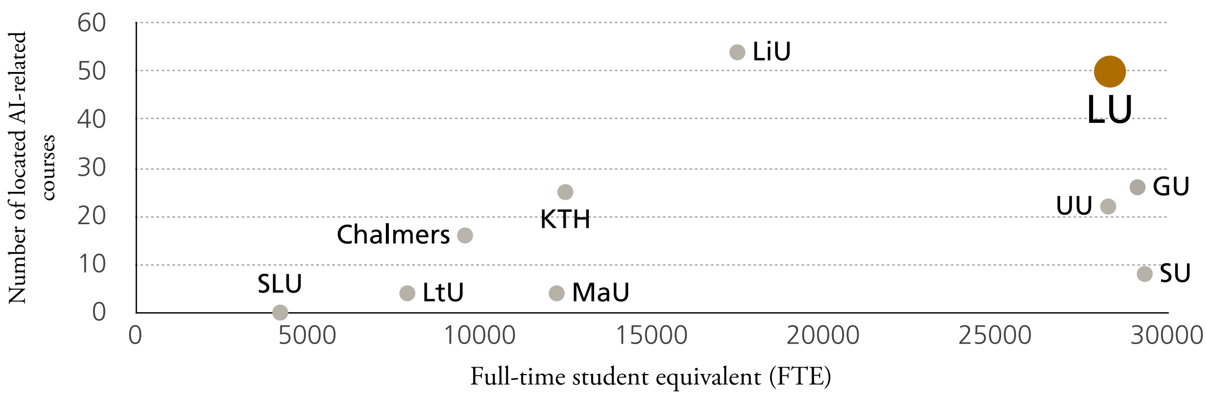
In this report, "footprint" refers to "course-technical" aspects (e.g., faculty home, level, credits etc), and how some of these aggregated metrics compare to the equivalent metrics for the university in question. This allows us to determine things like:

- the "weight" of AI teaching related to the size of the university (we use *full-time equivalent* (FTE) *[helårsstudent, HST, sometimes HÅS])*.
- how that weight compares to other studied universities, and to Sweden as a whole (or the Sweden represented by the selection of universities to be more precise).
- How different universities compare when it comes to the *level* of studies (bachelor-level vs. master level in this case).

4.3.2 Footprint comparison overview

We first plot data about number of courses and FTE in a diagram (diagram 4.1, below):

Diagram 4.1 Number of courses & university size



We initially hypothesised that there would be a strong correlation between general institution size and the number of AI-related courses, but that is not borne out by the collected data. Given Lund and Linköping data, we rather think that the size of the technical faculties (or equivalent, naming/organisation conventions differ) may a better explanation. Stockholm and Malmö both lack such specialised faculties.

The diagram also makes it evident to us that links to people with local knowledge are key to truly find all relevant courses – we simply don't think that it is a coincidence that Lund and Linköping, the two institutions where "bespoke digging" complemented the publicly available data (see next section), appear to offer many more courses than other comparably sized universities.

We have complained a bit about the data situation in Lund, and it is maybe not surprising that national data spread over a number of institutions and institutional solutions is at least as problematic. This is of course rarely a problem for an individual university, but national analyses that might be used to guide political education decisions suffer from such inconsistencies.

Following up on the discussion in section 3.2 (where we talked about the relative dearth of bachelor level courses in Lund), we then decided to look at the ratio between bachelor and master level courses in all studied universities. In the following two diagrams (4.2 and 4.3, below) we present this data both in absolute terms (number of courses) and as percentages. In the second diagram, we omit Luleå and Malmö[1] as they offer so few relevant courses that percentages would look distorted.

Diagram 4.2 Bachelor and master courses per university (#)

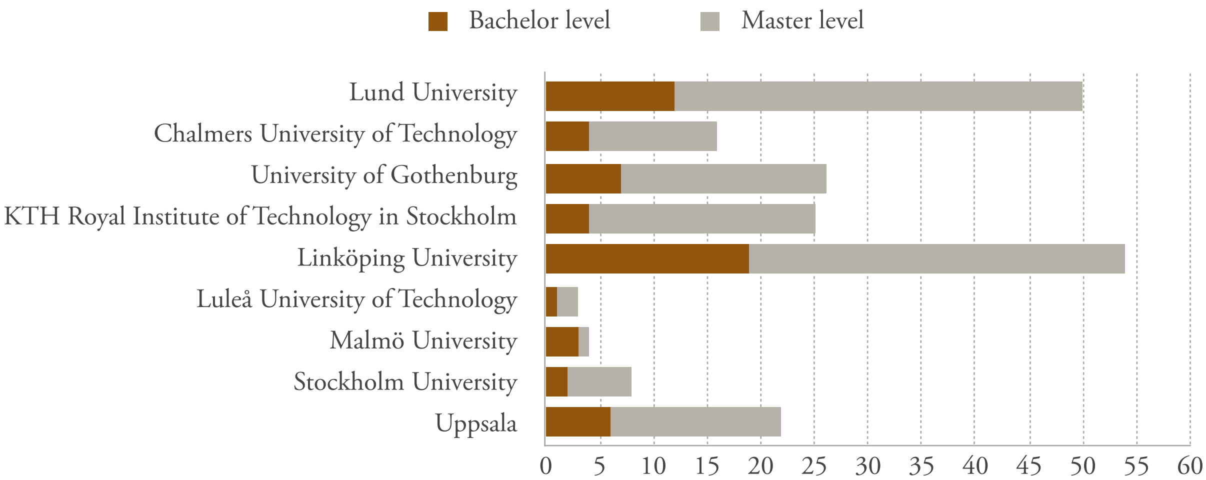
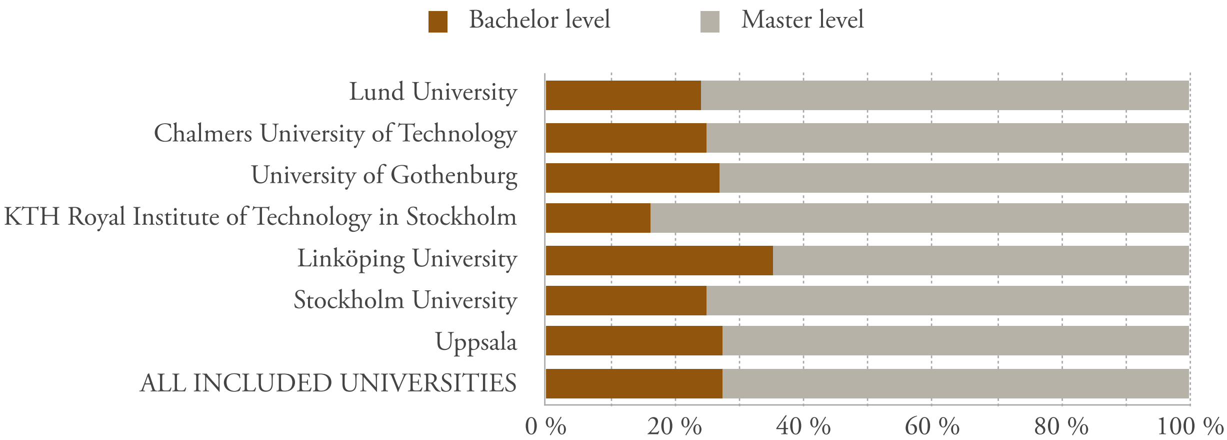


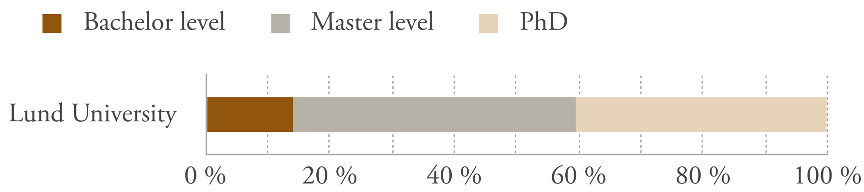
Diagram 4.3 Bachelor and master courses per university (%)



[1] In the case of Malmö University, we started that coding fairly early in the process, and was surprised by the low number of hits. We for that reason reached out to a contact at the university to help us investigate if we were missing something obvious – but it appears that we were not.

An invisible factor here is PhD courses. Had we added the thus far located Lund PhD courses (see section 3.6) to the LU tally, that particular bar would have looked like this (diagram 4.4, below).

Diagram 4.4 Bachelor, Master and PhD courses in Lund (%)



N.b. Hybrid master/PhD courses have only been coded as master courses in this diagram.

Given the apparent ration of bachelor courses compared to other levels, it continues to look to us as if undergraduate education initiatives can present some interesting strategic opportunities – with particular emphasis, perhaps, on bachelor-level programmes *which appear thin on the ground (see section 3.2).*

Potential data caveat

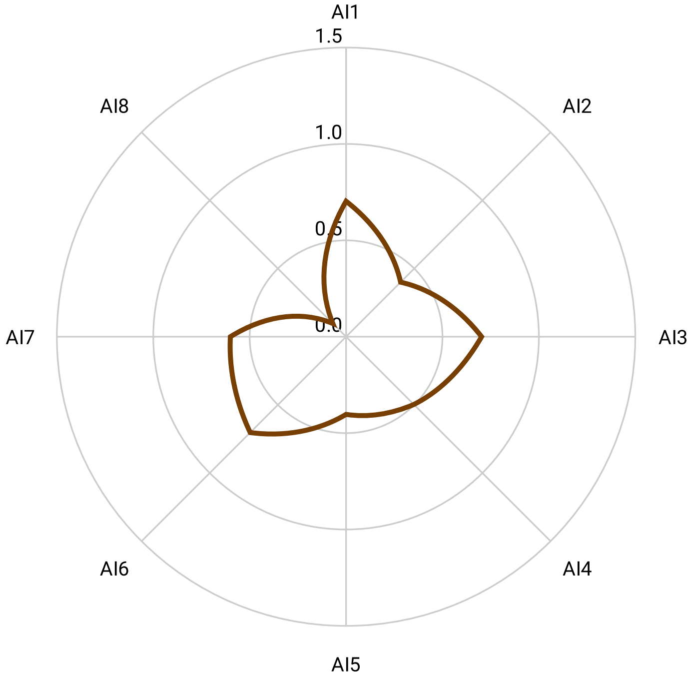
A potential concern is if bachelor-level courses are more "hidden" within set programmes (meaning we would not be able to find them using the adopted trawling methodology) in some universities than in others – such an eventuality might affect the relative strength of such strategic initiatives vis-à-vis other universities, but it would not affect Lund-internal considerations.

4.4 Fingerprint comparison

4.4.1 Introduction

Fingerprinting is when we use our *coded* data (see chapter 3) to detail what characterises a specific university in terms of AI-related education offerings, and so provide a unique"fingerprint" that can be used to compare different tertiary education institutions based on a finer-grained content analysis. To exemplify, for Lund we gather the averages of coding "scores" for each of the 8 categories for all (currently) 50 included courses, and end up with a "fingerprint" looking like this (diagram 4.5, below).

Diagram 4.5 Average of coded values for each category for Lund University (n=50)



For each category:
Strong = 3; Medium = 2; Some = 1; None = 0.

AI1 = Theory foundation
AI2 = Techniques/methods
AI3 = Solution complexes
AI4 = "Applied" (sciences)
AI5 = "Applied" (end-user)
AI6 = Impact on society
AI7 = Governing AI
AI8 = AI perceptions

On its own, fingerprints of this kind are of limited utility, but as a *comparison* tool they provide a quick and easily digestible overview. In this report we compare different universities, but it could conceivably be used in longitudinal analyses as well – to gather equivalent data for Lund University in a few years will give an idea of possibly changing focal areas, and impact of strategic decisions.

A caveat is that utility is contingent on good data – too limited a set of processed/coded courses for a case would make the resulting diagram less trustworthy. This has implications for a few of the studied universities, and when this happens (e.g., Malmö University), we will forego the diagrams and fall back on a purely qualitative discussion.

As Lund University is obviously our main concern, the Lund "fingerprint" will be overlaid in each radar diagram to facilitate quick visual comparison.

Comparison challenges and data quality caveats

Ideally, comparison data should be gathered using the same methodology throughout. Given the ambitions of this project, we have however devoted a lot of effort to conduct an exhaustive search for Lund University courses using a variety of sources and leads. This means that we have indeed located more courses at LU than would "organically" turn up in a like-for-like search. As we have mentioned, we have also initiated a collaboration with Linköping University, and our contacts there (Fredrik Heintz and Micael Frideros) similarly managed to get back to us with a list that was more extensive than the one we had managed to compile using externally available data sources.

However, we cannot see any clear biasing patterns – overarching distribution of courses according to our coding scores is not glaringly different when we compare the set we found "organically" in Linköping with the one that was boosted by Heintz and Frideros for instance.

The quality of the identification and sorting process is of course intimately connected with the quality of the data in the sources we use. We have found that course descriptions and learning outcomes vary a lot in terms of level of detail and language usage between universities. Keywords too are used very differently. Similar concerns were mentioned for LU-internal data, but that can at least conceivably be improved using stringent guidance and checks – the national situation is well beyond that kind of reach, and we cannot really see a way around that systematic deficiency.

In the next few pages, we will conclude this chapter with a brief university-by-university overview followed by a national ditto, as per:

A note about the diagrams

The bar charts present number of, as well as percentage of, courses that have been coded as including elements of the eight classification categories. It is important to note that a course can be registered as containing multiple such hits.

A few key takeaways

- Lund stands out in its (relative) focus on *links to society (*AI6-AI8). When starting the investigation, we actually thought LU had (relatively speaking) few such courses, but that thought is not borne out in a national comparison at least.
- Category AI8 *AI perceptions* stands out by its relative absence. We assume that related elements may be subsumed under other headings (a course titled something like *Dystopias in film and literature* would presumably include some related content).
- Linköping is the university with a fingerprint that looks most similar to Lund's, followed by the University of Gothenburg.
- Lund's and Linköping's dearth of courses spanning many different categories is notable in a national comparison.
- Linköping University's focus on ethical AI issues is notable.
- Uppsala University has more courses spanning many different coding categories than other universities.
- Chalmers's Machine Learning specialisation (relative to other course foci is notable).

We have gathered all course names for all case universities in Appendix 4. Reading through the lists will give a separate perspective when considering what Lund offers vis-à-vis what other institutions offer. Gaming AI architecture, eHealth, social media AI, and sports analysis are all examples of courses which do not seem to have immediately recognisable Lundian equivalents (although such elements are surely included in courses with other headings).

Fingerprint: Chalmers

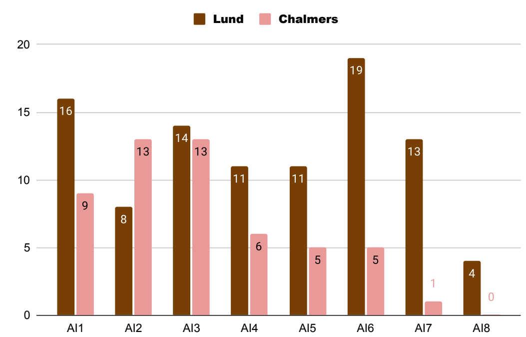
A special note: Chalmers and Gothenburg appear to share some courses. It might be worthwhile to investigate how such pooling of resources is done in practice, and if there is a strategic plan to complement one another based on comparative advantages.

CHALMERS
UNIVERSITY OF TECHNOLOGY

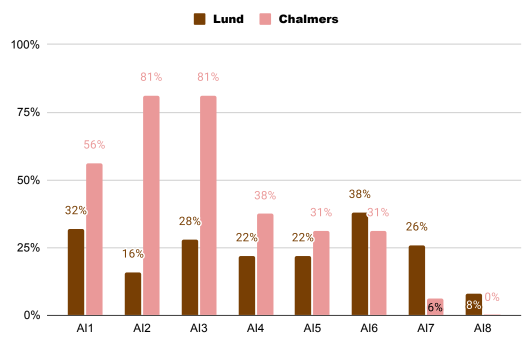
Chalmers (n=16), perhaps unsurprisingly, has a notable focus on technical aspects of AI (*fundamental techniques* in our coding language). Particularly *machine learning* is a notable focus: no fewer than 11 of the 16 included courses have Machine learning in their titles. This compares to six in Lund (with an additional seven PhD courses, not included in this tally).

Slightly more surprising is that Chalmers nevertheless offers a number of courses that stride divides to the other overarching classes (*application* and *links to society*, respectively). When we study such courses, we note that several appear to be hosted or co-hosted by the University of Gothenburg. This looks like a smart way to pool resources and in an area where there is perhaps a national scarcity of education capacity might make extra sense.

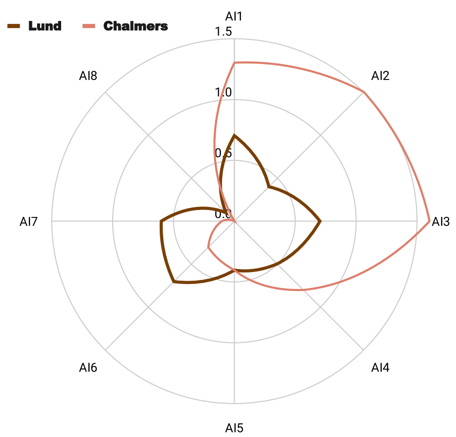
Number of courses coded as at least "some" for each category (out of total number of AI-relevant courses at that university)



Per cent of courses coded as at least "some" for each category (out of total number of AI-relevant courses at that university)

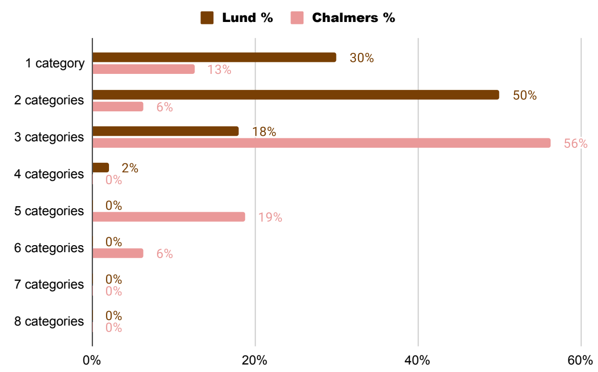


Average of coded values for each category



For each category:
Strong = 3; Medium = 2; Some = 1; None = 0.

Category spread (% of assessed courses for the university in question)



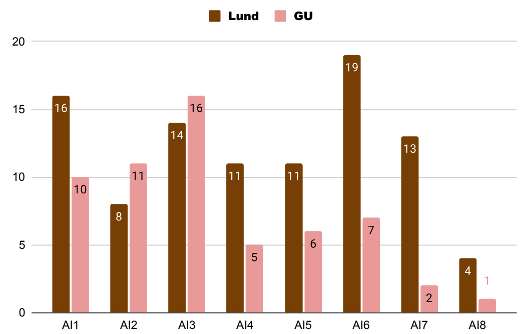
Fingerprint: University of Gothenburg

A special note: Chalmers and Gothenburg appear to share some courses. It might be worthwhile to investigate how such pooling of resources is done in practice, and if there is a strategic plan to complement one another based on comparative advantages.

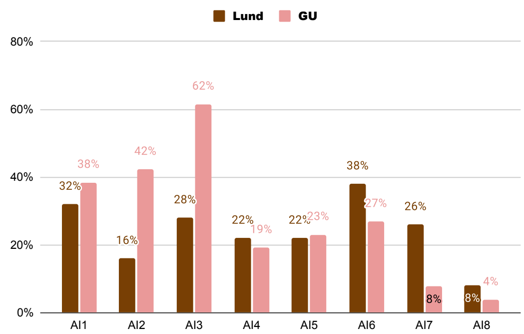
UNIVERSITY OF GOTHENBURG

Gothenburg (n=26) has a fingerprint that reminds of Lund's. A major difference is the relative focus on category AI3 *solution complexes.*

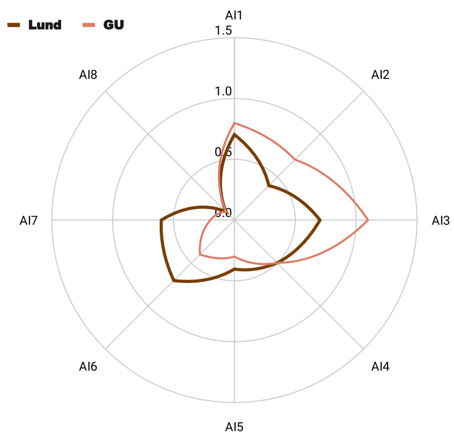
Number of courses coded as at least "some" for each category (out of total number of AI-relevant courses at that university)



Per cent of courses coded as at least "some" for each category (out of total number of AI-relevant courses at that university)

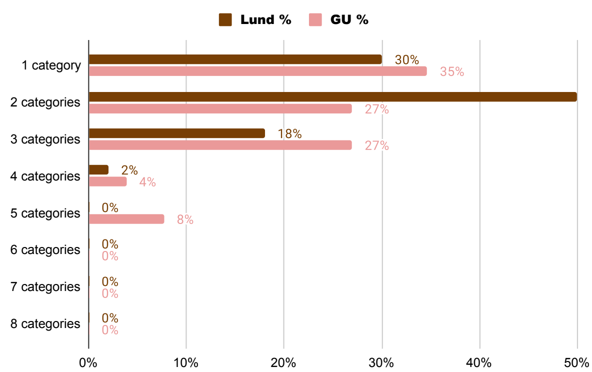


Average of coded values for each category



For each category:
Strong = 3; Medium = 2; Some = 1; None = 0.

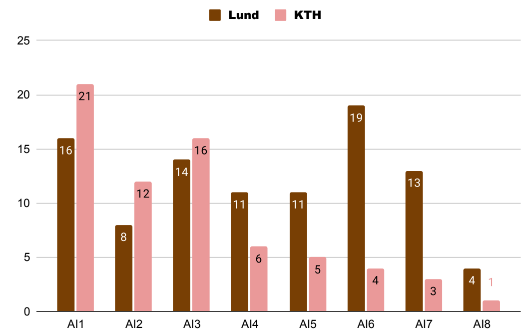
Category spread (% of assessed courses for the university in question)



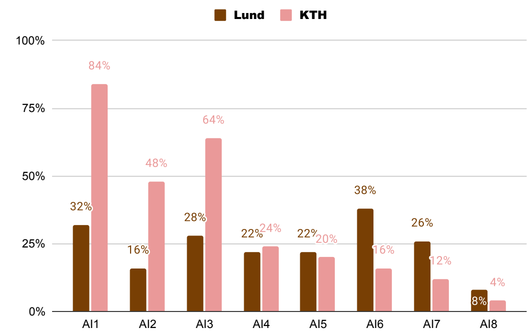
Fingerprint: KTH, Royal Institute of Technology

KTH (n=25) has a fingerprint uniquely focusing on the hard technological core of AI (category AI1, *fundamental techniques*). A comparison with Chalmers is interesting. Like Chalmers, KTH offers many machine learning courses and 15 out of the 25 included courses has *machine learning* in their titles. But beyond that, the term *deep learning* (djupinlärning) is referred to in five more course titles (one is overlapping with machine learning) – across all case universities that is only a major title component in three more courses. Examining full course syllabi bears out that this is a focal point: KTH offers more courses where deep learning is specifically mentioned in the syllabi than any other university. Chalmers, by comparison, offers a greater ratio of AI2 *techniques/methods,* and AI3 *solution complexes* (indeed to the point where the Chalmers fingerprint looks unique in this respect).

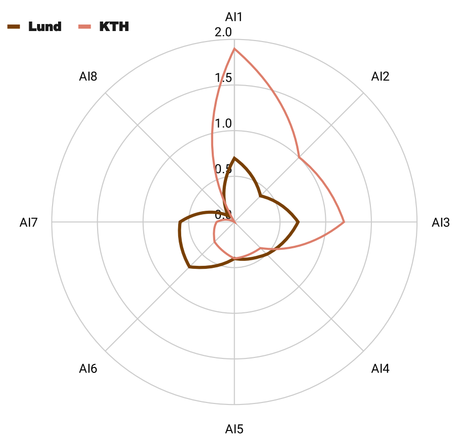
Number of courses coded as at least "some" for each category (out of total number of AI-relevant courses at that university)



Per cent of courses coded as at least "some" for each category (out of total number of AI-relevant courses at that university)

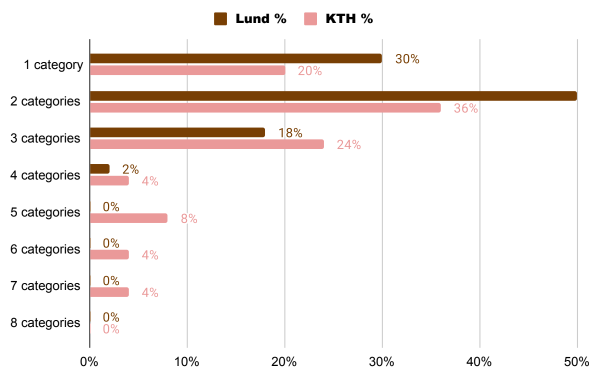


Average of coded values for each category



For each category:
Strong = 3; Medium = 2; Some = 1; None = 0.
Please note that we had to modify the chart scaling to fit the coding for category AI1 ***Theory foundation***

Category spread (% of assessed courses for the university in question)



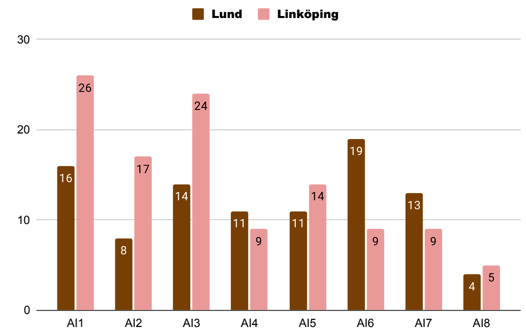
Fingerprint: Linköping University

A special note: our collaboration with Linköping University has yielded more courses than the methodology used elsewhere in this footprinting/fingerprinting operation would have. Absolute numbers are obviously affected by this, but we cannot see a clear bias in terms of relative distribution – but this methodological aberration still needs to be considered.

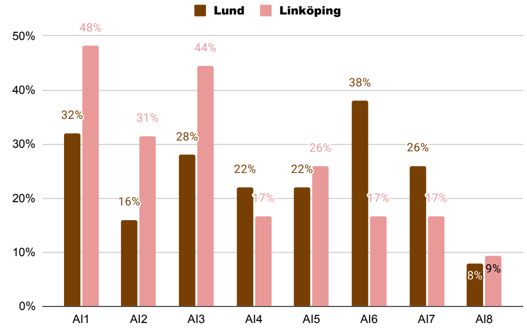
Linköping (n=54) has a fingerprint that closely matches Lund's, just slightly "shifted" towards the "techier" side of the radar chart. An interesting/curious observation is that Linköping is also similar to Lund in that it offers relatively few courses that span many different categories.

Ethical issues appear to be a particular focal point in Linköping: out of four courses explicitly mentioning ethics in the course titles, three are at housed in Linköping (the remaining in Lund). Other course clusters that stand out include one specialising in data mining, one focusing on eHealth, and one on smart cities.

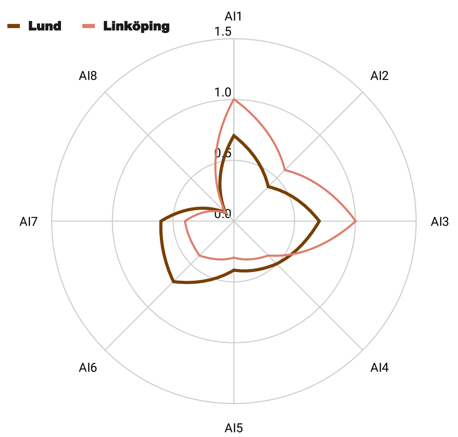
Number of courses coded as at least "some" for each category (out of total number of AI-relevant courses at that university)



Per cent of courses coded as at least "some" for each category (out of total number of AI-relevant courses at that university)

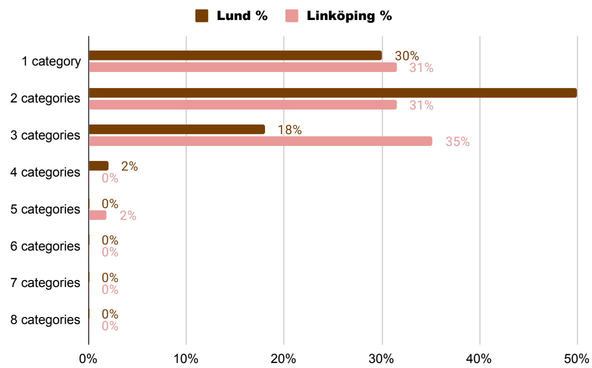


Average of coded values for each category



For each category:
Strong = 3; Medium = 2; Some = 1; None = 0.

Category spread (% of assessed courses for the university in question)



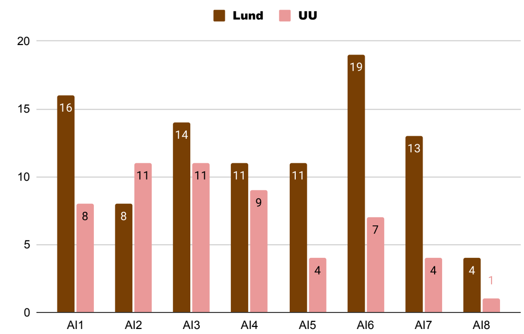
Fingerprint: Uppsala University

UPPSALA
UNIVERSITET

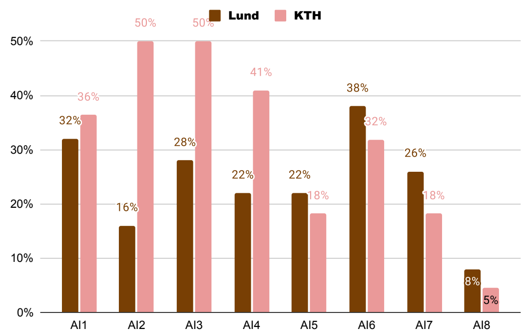
Uppsala (n=22) has a higher "score" for category AI4 *Applied (sciences)* than other institutions. Uppsala also stands out as a university that offers the highest proportion of courses spanning many different coding categories – the comparison with Lund is striking.

A particular course cluster that stands out involves AI for game programming (such aspects are included in other Swedish courses, but in Uppsala a few courses have that as the main theme).

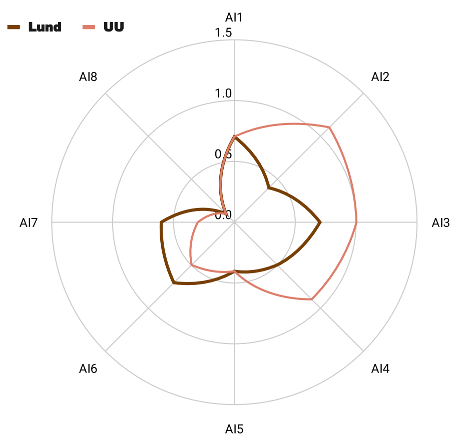
Number of courses coded as at least "some" for each category (out of total number of AI-relevant courses at that university)



Per cent of courses coded as at least "some" for each category (out of total number of AI-relevant courses at that university)

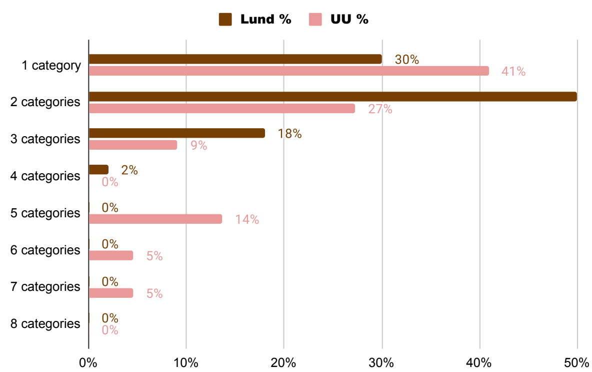


Average of coded values for each category



For each category:
Strong = 3; Medium = 2; Some = 1; None = 0.

Category spread (% of assessed courses for the university in question)



Fingerprint: Institutions with relatively few offerings

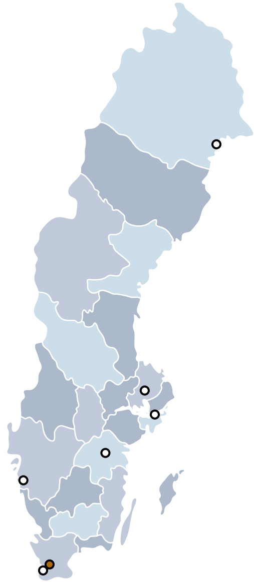
This group includes Luleå University of technology (n=4), Malmö University (n=4), Stockholm University (n=8) and the Swedish University of Agricultural Sciences (n=0). These institutions were grouped together under this heading as we decided on a cut-off point of 10 for chart presentations (n section 4.3.2 we speculated about the relative lack of AI-related courses in Malmö and Stockholm).

The STOCKHOLM courses we have found have a core focus on machine learning (six of the eight courses have that theme in the course names).

In MALMÖ, all four courses are technically oriented, with no coding for AI6-AI8 *links to society* (possibly surprising given that Malmö University has consciously set up a *Faculty of Technology and Society* to bridge those kinds of divides.

In LULEÅ, the only noticeable cluster is in deep learning. After we had locked the data set for the report late in May, two additional courses were noted (possibly resurrected syllabi), and one of these is also focused on aspects of machine learning. Like Malmö, Luleå offers one course where AI as part of game engines is explored. This is a relatively rare focus in the entire set of Swedish AI courses we have considered.

The SWEDISH UNIVERSITY OF AGRICULTURAL SCIENCES offers no AI-related courses that we could find using our default trawling methodology, but given that this was a bespoke lead, we intend to follow up on this before the publication of report 3.



Fingerprint: National (excluding Lund)

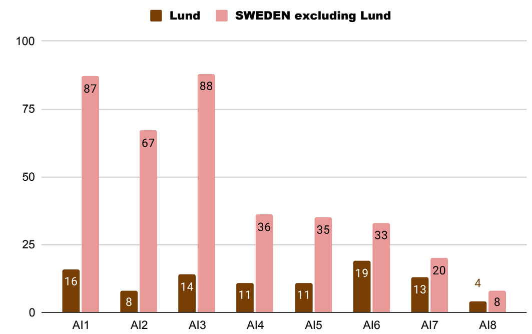
In this final fingerprint section, we aggregate all the considered Swedish courses outside of Lund (n=159) to see how Lund (n=50) stacks up in a national comparison.

As we have seen throughout, Lund stands out as the university with the relatively most prevalent focus on *Links to society* (AI6-AI8), with particular emphasis on categories AI6 *impact on society,* and AI7 *governing AI.* Indeed, combined with the fact that Lund courses rarely bridges the divide between *links to society* and the other two overarching categories (*fundamental techniques* and *application)* this would seem to explain much of the radar diagram-plotted shape difference between Lund and the others.

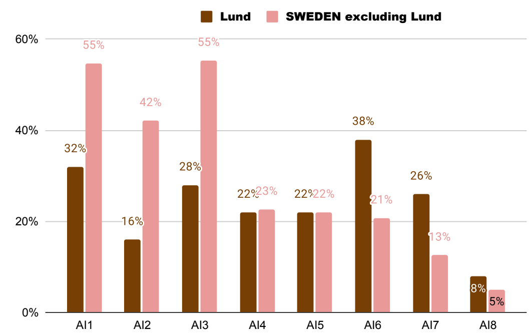
Machine learning seems almost "commoditised" as a course focus: it is prevalent all over Sweden. Good, solid courses in machine learning are clearly required as a baseline minimum, and students' university preference will for that reason hardly be based on that metric. More advanced or specialised machine learning or complementing AI profile courses are presumably stronger attractors if there is ever a situation where competition rather than collaboration is on the cards.

It seems to us that there is likely some strategic opportunities and room for manoeuvre if Lund would want to claim one or more specific profile "directions", but also that more internal LU collaboration to ensure bridging of category divides will probably be needed.

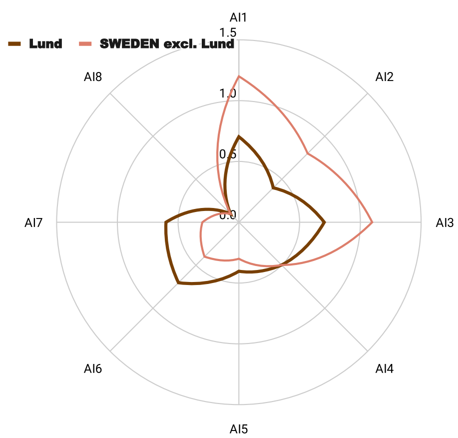
Number of courses coded as at least "some" for each category (out of total number of AI-relevant courses included in the national comparison)



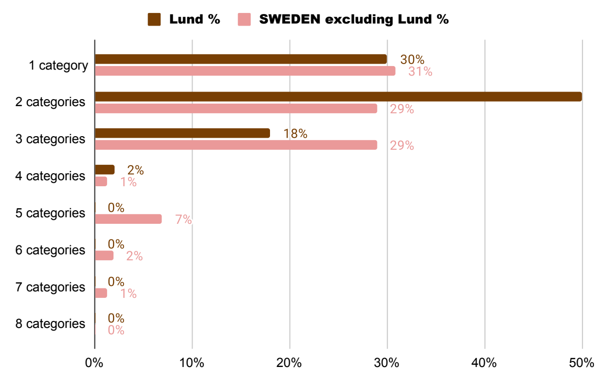
Per cent of courses coded as at least "some" for each category (out of total number of AI-relevant courses included in the national comparison)



Average of coded values for each category



Category spread (% of assessed courses for the university in question)



For each category:
Strong = 3; Medium = 2; Some = 1; None = 0.

5. AI teaching capacity @ Lund university: an update

5.1 Teaching capacity – a core project ambition

As previously described, one ambition of the project is to provide a clearer picture of the teaching capacity that exists when it comes to teaching courses in AI. There is so far no unified source of teacher data focusing on knowledgeability in specific fields, outside of departmental/disciplinary "home" which is of course a central identifier, and some local lists aiming to aid media to find relevant expertise. Aspects not neatly coinciding with departmental contexts are for that reason hard to keep track of. This is certainly the case with AI expertise which can potentially span the entire university, but fields like sustainability, diversity and much else would be similarly challenging.

In the current project, this situation leads to the following four ambitions (three primary, one secondary):

1) Locate as many of LU's AI-competent teachers as possible.
2) Code discovered teaching capacity according to our developed typology.
3) Disseminate this information as widely as possible to aid linkage opportunities
4) *(Secondary ambition)* Analyse the gathered data. While *presentation* of the located data in various ways is of course pivotal in order to facilitate linkage opportunities (without visibility, new connections are impossible after all), analysis of, say, teacher composition, faculty home etc. are considered more of a bonus at this stage. Given that we expect a significant tranche of new staff data (see blue box under section 5.2) we will postpone this exercise until report #3, expected in late 2021.

5.2 An updated list of teachers with AI competencies

The first report (December 2020) presented data from a survey sent out to identified teachers in the courses we had located. Some 32 respondents stated their willingness to appear in reports (like this one) to aid information dissemination and linkage opportunities (more respondents carried out the self-assessment, and were happy to let us use this data in aggregate analyses, but preferred to be left out of reports etc. where individual records were on show).

Between then and now, we have contacted more teachers based on various leads, and the tables below will list the most recent data that we have access to.

To gather relevant material, we have asked each respondent to self-assess his/her competence in AI-related matters, as based on our developed typology in order to catch the full gamut of potential takes on AI (each category was extensively introduced to make respondents able to interpret what we mean by each).

If they claimed knowledgeability in one or more of the eight AI categories, they were included in the final group of staff members that we then process and list in this report and elsewhere.

GDPR compliance note

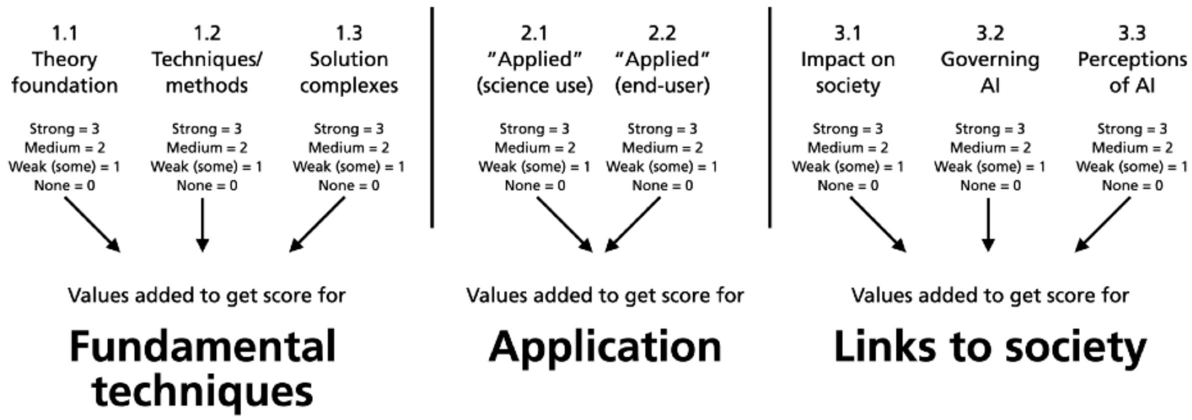
The data source is protected and stored locally at Lund University. All contact information etc. is sourced from LU's publicly available web site. The listed staff members listed below have **explicitly** consented to

a) have related data stored in the project database, and

b) be included in reports (such as this one) and other disseminated material.

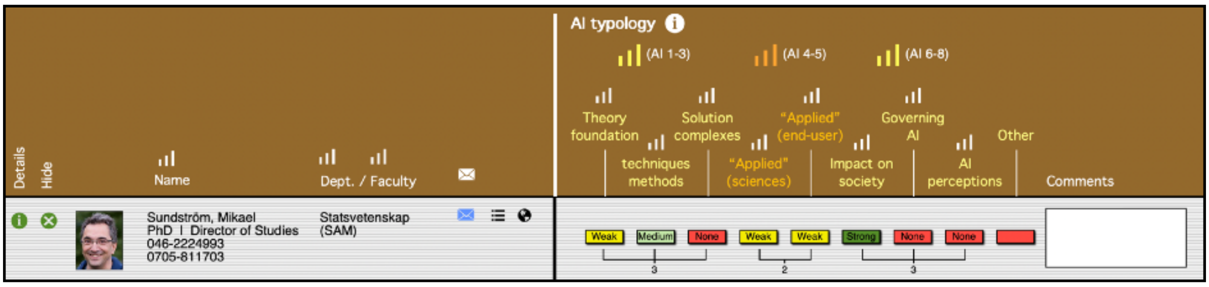
For each of the eight detailed categories (see figure 5.1, below), respondents could self-assess their proficiency as *strong*, *medium*, *some* or *none*. Technically, these answers were then converted to numerical values as per: Strong = 3; Medium = 2; Some = 1; None (or empty) = 0.

Figure 5.1. From category self-assessment to assessment scores



A typical database entry can look like this (figure 5.2, below).

Figure 5.2. Database management of self-assessment data (typical record, although with fake data). We also keep track of internal contact information and faculty home to aid later analysis.



The data is presented by means of three tables (tables 5.1, 5.2 and 5.3, below) – one per overarching category. Each table includes only staff members who have indicated some knowledgeability of one or more of the included sub-categories. Overlaps are of course inevitable for staff members who straddle divides between the larger categories, meaning that a teacher can be listed in more than one table.

Each table is in turn sorted into three self-assessed "levels" of expertise: "strong", "medium" or "some" – but it should be noted that even "some" is described in the survey as feeling confident taking on some teaching tasks in that field. The database allows for much more granular sorting/finding.

In report #3, this issue will be revisited, and a final updated list will be compiled. Meanwhile, the live database is available to our partners so that they can at all stages see the then current list, and search for specific competencies.

The three overarching categories (e.g., "Fundamental techniques") simply sum the calculated numbers to get a category score (see figure 5.1, below), which are in turn mainly there to aid pedagogical presentation.

Planned expansion

Staff data will very soon undergo a notable expansion. Our friends at AI Lund are in the process of distributing a survey to all its members, and they have graciously let us piggy-back our survey questions there. That means that a sizeable number of people with self-assessed AI-related expertise will be added to the equivalent tables in the final project report.

Table 5.1 – Fundamental techniques

First name	Second name	email	Homepage (if available)	Faculty
SELF-ASSESSED KNOWLEDGEABILITY: STRONG (aggregate assessment score > 5 and at least one subcategory assessed as "strong")				
Sonja	Aits	sonja.aits@med.lu.se		MED
Patrik	Edén	patrik.eden@thep.lu.se		NAT
Blerim	Emruli	blerim.emruli@ics.lu.se	https://www.lusem.lu.se/contact/bl5646em	EHL
Jasec	Malec	jacek.malec@cs.lth.se	http://cs.lth.se/Jacek_Malec	LTH
Mikael	Nilsson	mikael.nilsson@math.lth.se		LTH
Mattias	Ohlsson	mattias.ohlsson@thep.lu.se	http://cbbp.thep.lu.se/~mattias/	NAT
Magnus	Oskarsson	magnus.oskarsson@math.lth.se	http://www.maths.lth.se/matematiklth/personal/magnuso/	LTH
Krzysztof	Podgórski	Krzysztof.Podgorski@stat.lu.se	https://www.stat.lu.se/kontakt/mats-ksp	EHL
Markus	Ringnér	markus.ringner@biol.lu.se		NAT
Maria	Sandsten	maria.sandsten@matstat.lu.se	http://www.maths.lu.se/staff/mariasandsten/	LTH
Alexandros	Sopasakis	sopasak@maths.lth.se		LTH
Odd	Steen	odd.steen@ics.lu.se	https://www.lusem.lu.se/contact/ics-ost	EHL
Elin Anna	Topp	elin_anna.topp@cs.lth.se	http://cs.lth.se/topp-elinanna/	LTH
Pengxiang	Zhao	pengxiang.zhao@nateko.lu.se		NAT
Kalle	Åström	karl.astrom@math.lth.se	http://www.maths.lu.se/staff/kalleastrom/	LTH
SELF-ASSESSED KNOWLEDGEABILITY: MEDIUM (aggregate assessment score = 4 or 5, or both categories assessed as "medium")				
Bo	Bernhardsson	Bo.bernhardsson@control.lth.se		LTH
Mattias	Borg	mattias.borg@eit.lth.se	https://www.eit.lth.se/staff/mattias.borg	LTH
Anders	Brodin	anders.brodin@biol.lu.se	https://www.biologi.lu.se/anders-brodin	NAT
Lars	Harrie	lars.harrie@nateko.lu.se		NAT
Nils	Holmberg	nils.holmberg@isk.lu.se	https://www.isk.lu.se/nils-holmberg	SAM
Åse	Innes-Ker	ase.innes-ker@psy.lu.se		SAM
Andreas	Jakobsson	aj@maths.lth.se	http://www.maths.lu.se/staff/andreas-jakobsson/	LTH
Ali	Mansourian	ali.mansourian@nateko.lu.se		NAT
Niels Christian	Overgaard	niels_christian.overgaard@math.lth.se		LTH
Erik	Persson	erik.persson@fil.lu.se	https://www.fil.lu.se/person/ErikPersson/	HT
Behnasz	Pirzamanbein	behnaz.pirzamanbein@stat.lu.se		EHL
SELF-ASSESSED KNOWLEDGEABILITY: SOME (aggregate assessment score = 1, 2 or 3)				
Zheng	Duan	zheng.duan@nateko.lu.se		NAT
Alexander	Dürr	alexander.durr@cs.lth.se	http://cs.lth.se/alexander-durr/	LTH
Lars	Eklundh	lars.eklundh@nateko.lu.se	http://web.nateko.lu.se/personal/Lars.Eklundh/	NAT
Abdulghani	Hasan	abdulghani.hasan@nateko.lu.se		NAT
Maria	Hedlund	maria.hedlund@svet.lu.se	http://www.svet.lu.se/en/maria-hedlund	SAM
Markus	Lahtinen	markus.lahtinen@ics.lu.se	https://www.lusem.lu.se/contact/ics-lma	EHL
Stefan	Larsson	stefan.larsson@lth.lu.se	http://www.lantm.lth.se/medarbetare/stefan-larsson/	LTH
Vaughan	Phillips	vaughan.phillips@nateko.lu.se	https://www.nateko.lu.se/vaughan-phillips	NAT
Jörgen	Ripa	jorgen.ripa@biol.lu.se	https://www.biology.lu.se/jorgen-ripa	NAT
Benjamin	Weaver	benjamin.weaver@ics.lu.se	https://www.lusem.lu.se/contact/fek-bew	EHL
Ulrika	Wennersten	ulrika.wennersten@har.lu.se		EHL
Karl-Erik	Årzén	karl-erik.arzen@control.lth.se	http://www.control.lth.se/personnel/karl-erik-aarzen/	LTH

Table 5.2 – Application

First name	Second name	email	Homepage (if available)	Faculty
SELF-ASSESSED KNOWLEDGEABILITY: STRONG (aggregate assessment score > 3 and/or at least one subcategory assessed as "strong")				
Sonja	Aits	sonja.aits@med.lu.se		MED
Patrik	Edén	patrik.eden@thep.lu.se		NAT
Blerim	Emruli	blerim.emruli@ics.lu.se	https://www.lusem.lu.se/contact/bl5646em	EHL
Jasec	Malec	jacek.malec@cs.lth.se	http://cs.lth.se/Jacek_Malec	LTH
Ali	Mansourian	ali.mansourian@nateko.lu.se		NAT
Mikael	Nilsson	mikael.nilsson@math.lth.se		LTH
Mattias	Ohlsson	mattias.ohlsson@thep.lu.se	http://cbbp.thep.lu.se/~mattias/	NAT
Krzysztof	Podgórski	Krzysztof.Podgorski@stat.lu.se	https://www.stat.lu.se/kontakt/mats-ksp	EHL
Markus	Ringnér	markus.ringner@biol.lu.se		NAT
Alexandros	Sopasakis	sopasak@maths.lth.se		LTH
Elin Anna	Topp	elin_anna.topp@cs.lth.se	http://cs.lth.se/topp-elinanna/	LTH
Pengxiang	Zhao	pengxiang.zhao@nateko.lu.se		NAT
Kalle	Åström	karl.astrom@math.lth.se	http://www.maths.lu.se/staff/kalleastrom/	LTH
SELF-ASSESSED KNOWLEDGEABILITY: MEDIUM (aggregate assessment score = 4 or 5)				
Bo	Bernhardsson	Bo.bernhardsson@control.lth.se		LTH
Mattias	Borg	mattias.borg@eit.lth.se	https://www.eit.lth.se/staff/mattias.borg	LTH
Agneta	Gulz	agneta.gulz@lucs.lu.se	https://www.fil.lu.se/person/AgnetaGulz/	HT
Nils	Holmberg	nils.holmberg@isk.lu.se	https://www.isk.lu.se/nils-holmberg	SAM
Andreas	Jakobsson	aj@maths.lth.se	http://www.maths.lu.se/staff/andreas-jakobsson/	LTH
Markus	Lahtinen	markus.lahtinen@ics.lu.se	https://www.lusem.lu.se/contact/ics-lma	EHL
Stefan	Larsson	stefan.larsson@lth.lu.se	http://www.lantm.lth.se/medarbetare/stefan-larsson/	LTH
Erik	Persson	erik.persson@fil.lu.se	https://www.fil.lu.se/person/ErikPersson/	HT
Behnasz	Pirzamanbein	behnaz.pirzamanbein@stat.lu.se		NAT
Maria	Sandsten	maria.sandsten@matstat.lu.se	http://www.maths.lu.se/staff/mariasandsten/	LTH
Odd	Steen	odd.steen@ics.lu.se	https://www.lusem.lu.se/contact/ics-ost	EHL
Benjamin	Weaver	benjamin.weaver@ics.lu.se	https://www.lusem.lu.se/contact/fek-bew	EHL
Ulrika	Wennersten	ulrika.wennersten@har.lu.se		EHL

Table 5.2 – Application (cont'd)

SELF-ASSESSED KNOWLEDGEABILITY: SOME

(aggregate assessment score = 1, 2 or 3)

Anders	Brodin	anders.brodin@biol.lu.se	https://www.biologi.lu.se/anders-brodin	NAT
Zheng	Duan	zheng.duan@nateko.lu.se		NAT
Alexander	Dürr	alexander.durr@cs.lth.se	http://cs.lth.se/alexander-durr/	LTH
Lars	Eklundh	lars.eklundh@nateko.lu.se	http://web.nateko.lu.se/personal/Lars.Eklundh/	NAT
Helena	Elvén Eriksson	helena.elven_eriksson@nateko.lu.se		NAT
Lars	Harrie	lars.harrie@nateko.lu.se		NAT
Abdulghani	Hasan	abdulghani.hasan@nateko.lu.se		NAT
Maria	Hedlund	maria.hedlund@svet.lu.se	http://www.svet.lu.se/en/maria-hedlund	SAM
Åse	Innes-Ker	ase.innes-ker@psy.lu.se		SAM
Magnus	Oskarsson	magnus.oskarsson@math.lth.se	http://www.maths.lth.se/matematiklth/personal/magnuso/	LTH
Niels Christian	Overgaard	niels_christian.overgaard@math.lth.se		LTH
Vaughan	Phillips	vaughan.phillips@nateko.lu.se	https://www.nateko.lu.se/vaughan-phillips	NAT
Jörgen	Ripa	jorgen.ripa@biol.lu.se	https://www.biology.lu.se/jorgen-ripa	NAT
Karl-Erik	Årzén	karl-erik.arzen@control.lth.se	http://www.control.lth.se/personnel/karl-erik-aarzen/	LTH

Table 5.3 – Links to society

First name	Second name	email	Homepage (if available)	Faculty
SELF-ASSESSED KNOWLEDGEABILITY: STRONG (aggregate assessment score > 5 and/or at least one subcategory assessed as "strong")				
Markus	Lahtinen	markus.lahtinen@ics.lu.se	https://www.lusem.lu.se/contact/ics-lma	EHL
Stefan	Larsson	stefan.larsson@lth.lu.se	http://www.lantm.lth.se/medarbetare/stefan-larsson/	LTH
Ana	Nordberg	ana.nordberg@jur.lu.se		JUR
Erik	Persson	erik.persson@fil.lu.se	https://www.fil.lu.se/person/ErikPersson/	HT
Alexandros	Sopasakis	sopasak@maths.lth.se		LTH
Ulrika	Wennersten	ulrika.wennersten@har.lu.se		EHL
SELF-ASSESSED KNOWLEDGEABILITY: MEDIUM (aggregate assessment score = 4 or 5, or both categories assessed as "medium")				
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Mattias	Ohlsson	mattias.ohlsson@thep.lu.se	http://cbbp.thep.lu.se/~mattias/	NAT
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Odd	Steen	odd.steen@ics.lu.se	https://www.lusem.lu.se/contact/ics-ost	EHL
Elin Anna	Topp	elin_anna.topp@cs.lth.se	http://cs.lth.se/topp-elinanna/	LTH
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SELF-ASSESSED KNOWLEDGEABILITY: SOME (aggregate assessment score = 1, 2 or 3)				
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Lars	Eklundh	lars.eklundh@nateko.lu.se	http://web.nateko.lu.se/personal/Lars.Eklundh/	NAT
Agneta	Gulz	agneta.gulz@lucs.lu.se	https://www.fil.lu.se/person/AgnetaGulz/	HT
Lars	Harrie	lars.harrie@nateko.lu.se		NAT
Nils	Holmberg	nils.holmberg@isk.lu.se	https://www.isk.lu.se/nils-holmberg	SAM
Andreas	Jakobsson	aj@maths.lth.se	http://www.maths.lu.se/staff/andreas-jakobsson/	LTH
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Mikael	Nilsson	mikael.nilsson@math.lth.se		LTH
Behnasz	Pirzamanbein	behnaz.pirzamanbein@stat.lu.se		EHL
Jörgen	Ripa	jorgen.ripa@biol.lu.se	https://www.biology.lu.se/jorgen-ripa	NAT
Pengxiang	Zhao	pengxiang.zhao@nateko.lu.se		NAT
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6. Looking inward: a problematic data situation

6.1 The problem in brief

In this project we have had occasion to systematise answers to the following superficially simple query ideally directed to course coordinators:

"Hi. You are listed as a coordinator of course X. We ask you to answer the following Y questions about the course."

But:

1) Course data is stored in many different systems (the problem is compounded if we want to include PhD courses and courses that are programme-internal).
2) Coordinators (let alone teachers in courses) are not necessarily listed in any easily accessible (or any at all) LU-common systems.
3) We have to turn to a specific questionnaire system, add course data, coordinator data, and queries, and survey coordinators in that (highly laborious) way.
4) We have to establish a bespoke database to store and manipulate incoming data, and add links to any external systems.
5) Data required to identify and constrain the initial set of queried courses (e.g., keywords, learning outcomes texts etc.) are either treated wildly differently, or are not even available as an option (e.g., course content keywords).

What should be a relatively mundane information-gathering exercise is thus turned into an expensive, complicated and slow undertaking that because of these resource constraints can only be considered in a select few cases.

LU has a good historical track record of providing timely and needed education opportunities using tried and tested "devolved" analysis and decision-making strategies. Decision-makers at individual units would nevertheless surely benefit from an improved understanding what is being offered, and planned, in other parts of the sprawling University organisation as that would reduce redundancies and make evident where complementing capacity might be located.

For initiatives that somehow transcend organisational boundaries, this kind of information becomes exponentially more pressing. In certain cases, such as Lund University Commissioned Education (LUCE), a unit constantly working to match external demands to ever-changing resources across the entirety of the university, the issue is existential.

In the following, it is assumed that it would be strategically desirable to boost LU's general capacity to query the entire organisation quickly and efficiently, as outlined above. We fully realise that investment costs would have to be absorbed and weighed against projected benefits, but will not presume to make any such weighing ourselves. We hope to return to this issue further in report #3, where the idea is to *very* tentatively indicate some associated investment costs.

6.2 Querying Lund University internal data: an analytical headache

In essence, LU-wide expertise capacity assessment tends to boil down to three distinct questions:

- What do we offer in terms of *research* about X?
- What *education* do we offer about X?
- What *staff capacity* do we have access to regarding expert area X?

Some associated problems are of course "research-technical" in character. How can X be understood and typologised? What do we mean by "research" in this context? How should "education" be delimited in this particular case? What is in fact "staff capacity"? Is a recognised expert who has no time to spare for new projects to be considered available or "dormant" capacity for instance? Etc. etc.

Such challenges are part of any serious research endeavour, and while it might for example be possible, indeed desirable, to model default "takes" on some of these issues (defining and classifying what we mean by "education", or adhering to a quality-assured set of keywords, say) and strive to use these across a variety of investigations, we should normally both expect and accept associated costs in any inward-looking investigation.

Other costs are harder to justify if we seriously and regularly wish to assess what we do as a University. Such exercises perforce entail gathering and meshing data about staff, projects, courses, programmes and more, and then (in most cases) adding relevant meta-data to these basic building blocks to help analyse and glean new insights about specific aspects.

In the best of worlds:

1) Foundational University data sources are coherent, reliable, easy to access, contain relevant and up-to-date core data (including certain metadata, such as content-specifying keywords), and are "aware of" (linked to) complementing data repositories where pertinent.
2) It is easy to locate and move from data source to data source where links are apparent (who teaches in a given course, or which researchers are members of a specific research project for instance) with the aim to extract existing foundational data with a minimum of effort.
3) It is easy to add and manipulate metadata on top of foundational data to aid higher-order aggregation and analysis.
4) It is easy to initiate "queries" that will provide or update foundational data or new metadata. For example, it should be easy to survey staff about their perceived expertise in a certain area, and similarly easy to locate who might know the details about a specific course, programme, research project or staff role.

All of these listed items are currently problematic at Lund University. We use a welter of different data sources and systems designed to solve one or many problems (and that may be well-designed for that purpose), but rarely to aid University-wide analytical efforts. Data sources are often set up with little apparent heed for any overarching informational architecture, except to the extent required to complete the immediate task(s) at hand. Information redundancy, information gaps, vague or non-existent links between complementing data sources and inconsistent user interfaces are rife. Metadata addition is possible in certain sub-systems (such as LUCRIS – that will be discussed more below), but not in others, and there is certainly no organisation-wide aggregation level where metadata and the analysis of such metadata could be a design priority. There is no way* to "auto-query" (i.e., have IT systems assist with queries) staff for complementing data other than by laborious setting up of special questionnaires and then somehow store and manipulate the gathered responses in separate, bespoke, and likely transient data sources (often in Excel files, we venture to guess).

*) **Caveat**

Processes have evolved to encourage staff to update LUCRIS data, and to enter required information about secondary employments and the like, usually through the "human chain of command" where department managers (equiv.) ask staff to make updates in the relevant systems.

This method (with its intrinsic informational flaws) seems to be employed on the "system internal" level – i.e., diligent staff members log into specific systems and make updates upon request. We have found no evidence of organised ways to gather and store meta data at anything looking like a proper aggregation level.

6.3 Suggested remedies #1: improved IT system support

6.3.1 Solution variant 1: the hopeless Big Bang Theory

Viewed from a high altitude, the obvious solution would seem to be a top-to-bottom overhaul of how we store, manipulate, and use core data. A big bang of change leading to a monolithic system containing staff data, education data, research data (and all relational links between these), with plenty of options to add and edit metadata to all data nodes, and an included "enquiry engine" aiding questing analysts when they wish to ask easily identifiable respondents about their research, their expertise, their teaching, their managerial roles, their plans ahead etc. LUBAS, LUCAT, LUCRIS, the LTH course database, RETENDO and many many other data sources, merged into a shining new LUNIRVANA system, complete with analytical add-ons. What's not to like?

Any IT person worth her salt would rightly shudder at such a Frankensteinian suggestion: what looks fantastic on paper would almost unavoidably mean extended anguish across the entire organisation, exorbitant costs and uncertain end results: this is a rabbit hole you can follow to the depths of the Earth, and pour endless resources into.

6.3.2 Solution variant 2: "LU Analytics" as a data aggregation + metadata layer

One way to attenuate the problem of dissociated data sources and lack of metadata manipulation options would be to create a separate data source specifically designed to regularly import/mirror existing core data about staff, education activities, research projects etc. from existing data sources, and then add options to enter and manipulate complementing data as desired. Such an *LU Analytics* database would minimise disruption to the core tasks that existing data sources are designed to handle, while making available much of the outlined utility.

It would still be a sizeable enterprise: the *LU Analytics* database would have to be established, integration strategies would need to be explored to allow the regular importing of data from all relevant data sources; ways to aid actual surveying would have to be developed (maybe using integration with existing survey tools); metadata handling and security would have to be analysed, then settled; organisation processes would have to define who can do what in the new system; long-term archiving strategies and data retention (or deprecation) policies would have to be in place.

Still, this should be accomplishable and can be subdivided into different phases where tools and processes are gradually rolled out to eventually furnish the full projected utility.

6.3.3 Solution variant 2b: LU analytics plus leveraging certain foundational data sources

The complexity and "thickness" of the "LU Analytics" layer of data mirroring + metadata will be notably affected by the information-architectural thinking that has gone into – or not – existing data sources. Particularly LUCRIS seems to have a lot of analytical potential built in, and allows for efficient, flexible and quality-assured storage of metadata about researchers and research activities. The creation of an *LU Analytics* layer might in that particular case be helpful if it includes query engines: garnered metadata about research activities might in this case at some point be fed back into LUCRIS which lacks, or keeps inactive, features of this sort (e.g., an integrated way to automatically generate surveys). In any case, depending on means of access and available APIs, the *LU Analytics* layer needs to integrate with other data sources in bespoke ways to make sure to reduce redundancy to a bare minimum, and make sure existing analytical utility in other systems is leveraged whenever possible. A challenge would be that reliance on *LU Analytics*-external analysis systems would require a readiness to "roll with the punches" if and when these external systems are somehow changed or deprecated.

6.4 Suggested remedies #2: Syllabus data stringency improvements

Having reviewed many hundreds of syllabi across Lund University (and even more beyond LU), we can state with some confidence that standards vary wildly when it comes to the structure and content of such texts. Yet these texts are the only nominally equivalent data sources available when analysing content and focus. There are active attempts at harmonising the "genre" (e.g., the faculty course syllabus group at the Faculty of Social Sciences, and similar organisational solutions elsewhere), but with so many different authors scattered across the entire organisation such data harmonisation will inevitably be hard to guarantee.

A potential part-remedy might be to implement a stringent system of keywords maintained and quality-assured by the libraries' information systematisation staff.

6.5 PhD course data as a special case

As mentioned in section 3.6, the data situation pertaining to PhD courses seems particularly unfavourable when it comes to LU-wide analysis. Some courses are detailed in central systems (and we have listed what was easily locatable in the table in that section), while others, given on the department level, are not.

We would recommend an obligatory, pan-LU duty to at least register PhD courses in a common repository (LTH can potentially be an inspiration here) as they are established/run, and to include a baseline minimum of data, including name, year, term, number of credits, involved teachers and a brief descriptive text.

We recognise that any administrative additions will likely generate political opposition in some quarters, and that this needs to be taken into account and addressed – including by strong assurances that this is intended to facilitate overarching future strategic analysis, and not as a possibly ominous embryonic managerial steering tool. Processes must also be made as simple as possible and forego the temptation to demand information which is not obviously needed for analytical purposes – keeping overhead to a minimum is key.

Appendix 1: The analytical framework – a recap

In report #1, we explained how our analytical framework with its three overarching, and eight secondary dimensions/categories has been designed. Because each report is intended to be a freestanding product, a very slightly abridged version of that chapter is furnished in this appendix.

In this report, the ambition is indeed to catch as much of the total breadth that we can, from deep-under-the-hood technical fundaments to how AI is perceived or presented in general societal debate or even fiction – as all those aspects can and are discussed, and potentially taught, under the generous "AI" banner.

Our solution has been to attempt to establish a typology comprising AI-related topics/fields that *together* cover the entire gamut of conceivable term usage scenarios. We spent serious time and effort on it and have tried it on numerous stakeholders before settling on its current form.

The framework comprises three main categories, which each have a set of sub-categories.

A1.1 Overarching category #1: **fundamental techniques**

This is a category intended to capture technical under-the-hood aspects; elements that together make AI in some applied form possible.

Sub-category 1.1: Theory foundation

With apologies for the simplification, we might use transportation technology as an analogy: transportation tech makes use of a range of fundamental physics and engineering principles, concepts, paradigms etc. Internal combustion and mechanical power transfer principles can be studied isolated from any desire to relate to transportation or vehicle development. Similarly, scientific insights from a variety of fields (e.g., computer science, statistics, neuroscience) that are crucial in AI systems can be and are studied without a guiding "AI development imperative".

Sub-category 1.2: techniques/methods

At some point a number of such fundamental building blocks are assembled/combined into an at least theoretically viable *system* where AI as an approach (in some form) is the explicit design ambition. The imperfect transport analogy might be the developing of a viable drivetrain based on the many insights gleaned from fundamental research and established principles.

Sub-category 1.3: solution complexes

The perceived potential offered by this system or a combination of systems are finally made to address a particular larger-scale problem or category of problems. Examples could include Computer Vision, Natural Language Processing and Voice Recognition. The transportation analogy (yes, still imperfect as most analogies tend to be) could be transportation over land, on and under the sea or airborne; manual or automatic etc. etc. The most important thing is that a problem is now at the forefront, and AI techniques and methods are perceived as viable solutions or sub-solutions.

A1.2 Overarching category #2: **application**

Here the focus is where AI has been commoditised and so turned into usable tools – maybe as applications or APIs where fundamental understanding of what is happening under the metaphorical hood is not necessary to be able to extract utility from the underlying systems. In the trusty transport analogy, we would now be at the *vehicle* stage, where users can operate complex systems without any detailed, or indeed any, knowledge of how they actually work.

Sub-category 2.1: "applied" (sciences)

Some AI applications can be used as special tools to further scientific research – an archaeologist might be able to use an app to analyse drone data of a landscape to find indications of roads or buildings for instance. We decided to detach such usage, and how it is possibly being taught, as we provisionally assume that such users will often be better acquainted with the *fundamental techniques* aspects, and be included in closer feedback loops with that overarching category. This potential interface between the two categories seemed important to try to keep track of.

Sub-category 2.2: "applied" (end-user)

This is expected to be the much larger of the two sub-categories: apps and systems with user interfaces expressly hiding much of the underlying complexity, meant for businesses or even consumer use.

A1.3 Overarching category #3: **links to society**

AI will impact society in a range of ways, and those effects will need to be understood in order to organise relevant governance principles, and understand ethical implications. But AI is also *perceived* in different ways in society, through literature and other cultural communication channels. To wrap up the transport analogy, the impact on society of cars or air traffic, and the need to regulate these new aspects, and how they are understood in society would be the equivalent here.

Sub-category 3.1: Impact on society

The effects of AI on communities, markets, individuals, organisations or other parts of society, both long-term and short-term. This could include filter bubbles, polarisation, surveillance, dictatorships, democracy, economic growth, business innovation, trust, employment and/or production where AI and its mechanisms is specifically studied as a cause.

Sub-category 3.2: Governing AI

How AI is regulated by hard and soft law, such as law, practice, policy, standardisation, and recommendation. Examples may include ethics guidelines, big data regulation, data protection laws, organisational policies on AI methods and usage, aimed at governing AI in one way or another.

Sub-category 3.3: AI perceptions

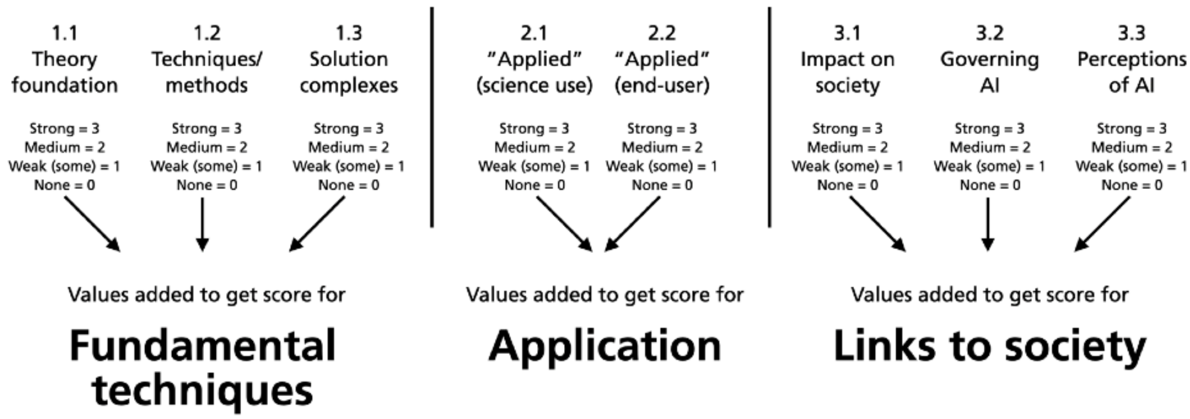
This area concerns representations and conceptions of AI in the past and present. Examples include AI in religion, ethical concerns from a philosophical perspective, AI in media and AI in literature and art.

A1.4 Extra category #3: **other**

Realising that some empirical data might prove not to fit the thus pre-conceived categories, we have added an "other" category to store such potential instances, and use them to guide later framework evaluation and (possible) revision work. *This has so far not been needed.*

The framework and its typology is used throughout the project to maintain consistency. For each staff, LU course and extra-LU course record, we mark up the subcategories as in in evidence (or not): *strong, medium, some* or *none.* Each notification is then associated with a numerical *assessment score* (se figure A1.1, below) which can be used in further analyses:

Figure A1.1. From category self-assessment to assessment scores

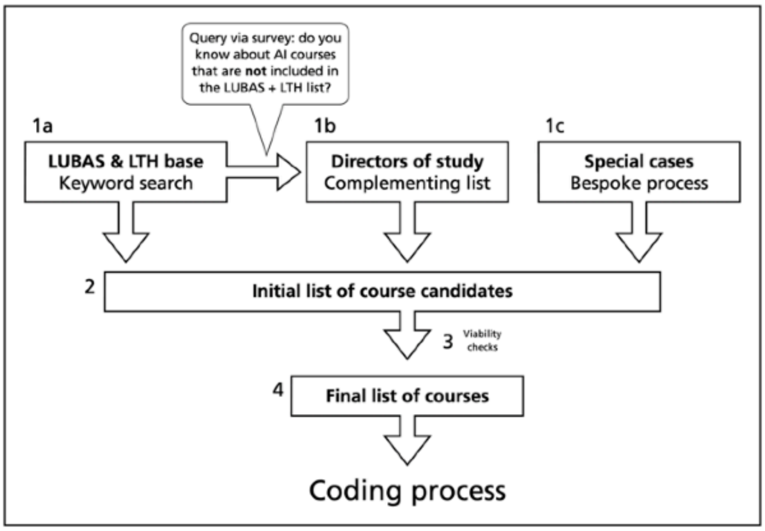


Appendix 2: Explaining the course data gathering method

A.2 Locating relevant Lund courses to survey

Figure A2.1, below, provides an overview of the identification process for Lundian courses. Each step will then be presented in turn.

Figure A2.1 Course identification methodology



First (1a), we have been been conducting course syllabi keyword searches. To ensure that we used a relevant set of keywords, we initially consulted a group consisting of researchers who work with AI in various fields and disciplines. In the “training phase” (autumn 2020) we then specifically examined which keywords provided most solid hits, and these were then used in the comparative effort in this report.

We have specifically looked for courses running in 2020 and spring 2021 to keep data steady, and aid comparative analysis. In report #3 this will be relaxed and some later courses that we have already noted are inbound will then be added (as far as we can tell, these additions will not materially alter the analysis as it looks in this report, but that of course remains to be seen).

A major part of this work has been the *second* step (1b) where we sent out a survey to directors of study. Questions we asked included:

> in your view, do the courses we list (the lists contained subsets of courses that the Director in question should be familiar with) contain AI elements? If not: which courses can be deleted from the survey and why? Are there *additional* courses beyond those we have listed that in your view include AI elements? If so: which ones (please provide details)? Are there any plans for *new* courses with such a focus? What *teachers* are working, or will work, in these courses.

This step was intended as a secondary net with which to catch relevant courses and exclude unreasonable ones.

Aided by the survey answers, we then finalised the list of Lund courses that we have proceeded to code for type of AI content (see Appendix 1). A final checkpoint was the actual coding process itself: if the coding yielded no linkages to our AI categories, the course was removed from the list of viable candidates.

Locating relevant courses to survey outside Lund

For courses outside of Lund, we have for the most part used a syllabi search, using a set of key terms that proved particularly effective in Lund: AI, artificial intelligence, deep learning, machine learning, big data, image analysis, automation, neural network, robotics – and related forms (words beginning w. "neu" to catch forms of "neural" for instance) plus the equivalent Swedish terms. Is this enough? We did catch a sizeable number of courses using this trawling methodology and that could be construed as a measure of success. On the other hand, the multi-pronged approach in Lund, and a similarly comprehensive investigation in Linköping (see chapter 4) yielded still more courses. Based on that, we believe that intimate knowledge of each institution and its data idiosyncrasies would be the only way to ensure a notably more complete data set.

We had the opportunity to compare the Linköping dataset that was so to speak found "organically" using our default keyword searches, and the more complete set produced with the help of our friends in Linköping, and could at least not see any suspect bias in the smaller set when we proceeded to code the courses. Whether this holds true for the other universities is not possible to say of course.

Appendix 3: The analysis database as a project deliverable

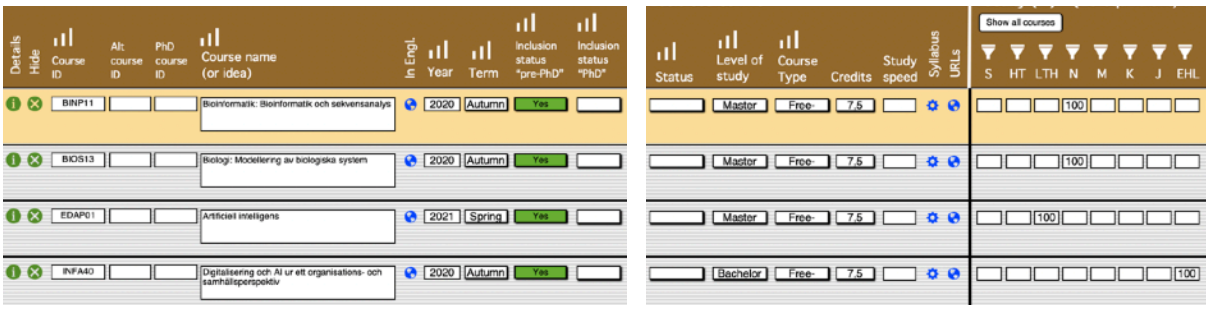
The data we are working on and with is *highly* volatile. Yet a main priority is to facilitate the exchange of the freshest information available. Our solution is to give selected partners access to the live database we are using to gather and analyse information. The database contains all LU, national and international courses we have considered for inclusion in the coding phase and, for the LU courses, all teachers that we have been able to locate that are associated with these courses – and more staff with relevant AI competency. For staff data, we only store information that is publicly available on LU web pages, and/or teachers who answer our queries about self-assessment of AI-related expertise (surveyed teachers are of course given the option to forego inclusion of that information in the final data set).

The data set *could* potentially be limited to project-internal analysis, as in most research efforts. That would mean regular reports (see previous chapter) where fundamental data would be secondary to what can be gleaned at the aggregate level.

For that reason, the database itself is designed to be immediately usable by selected partners outside of the core project group. The screenshots below (figures A3.1 – A3.3) are intended to give an idea of how users interface with the data. Sorting, finding and combining are design priorities to quickly probe different combinations of courses and included staff members.

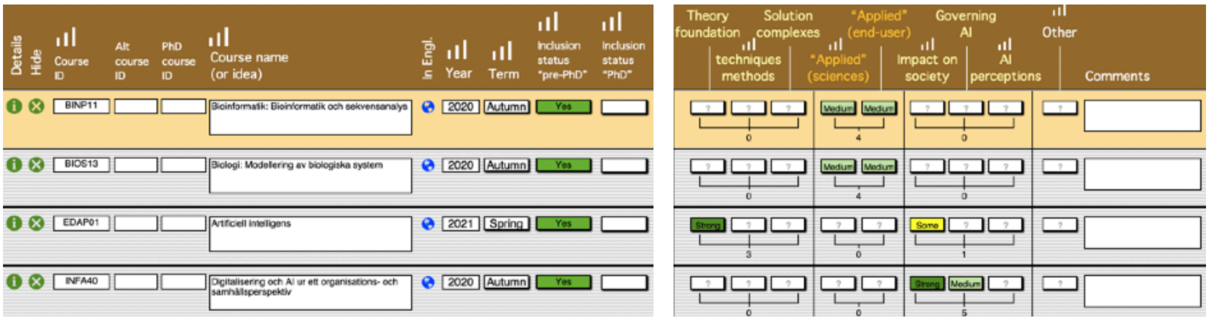
A3.1 Course data examples

Figure A3.1 Storage of fundamental course data and faculty home (for LU courses)



- The database contains links to related web pages, syllabus texts etc.
- A separate details pane stores information about teaching teams and other pertinent information.
- Faculty home are represented in percentage form

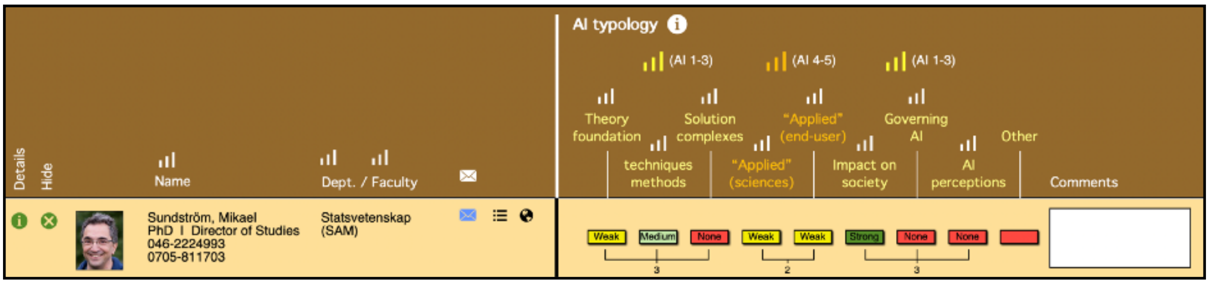
Figure A3.2 AI focus according to project typology



- As can be seen, a course can be coded as having multiple foci, and we attempt to gauge the "intensity" of each based on syllabus information. This was discussed in Appendix 1.
- We can also see how "scores" are aggregated to form representation scores for the overarching categories. *Theory foundation, techniques/methods* and *solution complexes* for instance makes up the overarching category *fundamental techniques.*

A3.2 Staff data example

Figure A3.3 Staff members with self-assessed AI competency



- This example uses fake data (project member Mikael Sundström has nowhere near this AI-related proficiency!) to demonstrate how data is being managed.
- The many sorting options is to make it easier to quickly home in on the sort of proficiency a user is looking for.
- Department home is also used to automatically detect faculty home to aid future aggregate analysis.

Appendix 4: List of course names

Below we provide two lists – one comprising all included Lund courses (including PhD ones), the second presenting all other included Swedish courses. We only furnish course names + level (+ university in the second table) as the main idea is that the tables can possibly provide some inspiration when comparing LU plans to what is readily available in several Swedish universities.

A handful of LU courses are still being investigated actively, as we have found data inconsistencies relating to (for instance) level of study, and the final report (report #3) will take any resulting changes into account.

Lund courses

AI i samhället	Master
AI och samhälle: juridiska, etiska och samhällsrelaterade aspekter av AI	PhD
Artificial Intelligence in Medicine and Life Sciences – AI for Image and Video Data	PhD
Artificial Neural Networks and Deep Learning	PhD
Artificiell intelligens	Master
Artificiell intelligens inom medicin och livsvetenskap	PhD
Autonoma system	PhD
Autonoma system del 1	PhD
Autonoma system del 2	PhD
Bayesian Methods	Bachelor
Beskattning i den digitala eran	Master
Bildanalys	Master
Bildanalys	PhD
Bildanalys för doktorander	PhD
Bioinformatik: Bioinformatik och sekvensanalys	Master
Bioinformatik: Programmering i Python	Master
Biologi: Modellering av biologiska system	Master
Datorseende	Hybrid Master and PhD
Deep Learning och GANs	PhD
Den smarta stadens styrning: AI och etik i en spatial kontext	Master
Digi MTOS - Det digitala mötet mellan människa, teknik, organisation och samhälle	PhD
Digitala kulturer: Teorier - Introduktion	Bachelor
Digitalisering och AI ur ett organisations- och samhällsperspektiv	Bachelor
Europeisk dataskydssrätt	Bachelor
Europeisk patenträtt	Master
Finans: Finansiell ekonometri	Master
Grafiska modeller, Bayesiansk inlärning och statistisk sambandsbaserad inlärning	PhD
Handelsrätt: Rättsliga aspekter på artificiell intelligens	Bachelor
Immaterialrätt, digitalisering och artificiell intelligens	Master
Inlärningsteori och förstärkningsinlärning	PhD
Intelligent Autonomous Systems	Master
Introduction to Machine Learning, Systems and Control	Bachelor
Introduktion till artificiella neuronnätverk och deep learning	Master
Introduktion till deep learning	PhD
Introduktion till maskininlärning	PhD
Juridik och Artificiell Intelligens (AI)	Bachelor
Kognitionsvetenskap: Neuromodellering, kognitiv robotik och agenter	Master

Kognitionsvetenskap: Teorier och modeller i kognitionsvetenskap	Master
Linjär och kombinatorisk optimering	Hybrid Master and PhD
Maskininlärning	Hybrid Master and PhD
Maskininlärning	PhD
Maskininlärning	PhD
Matematisk statistik: Linjär och logistisk regression	Master
Matematisk statistik: tidsserieanalys	Master
Medicinsk bildanalys	Hybrid Master and PhD
Medicinsk rätt	Master
Minnesteknologi för maskininlärning	Hybrid Master and PhD
Modelling and Learning From Data	Master
Monte Carlo and Empirical Methods for Stochastic Inference	Master
Neuroteknik	Bachelor
Nonparametric Inference	Master
Optimering	Hybrid Master and PhD
Optimering	Hybrid Master and PhD
Optimering för maskininlärning	Master
Programmeringsmodeller och metoder för att hantera stora datamängder	PhD
Projekt i autonoma system	PhD
Projekt i system, reglering och maskininlärning	Master
Radar och fjärranalys	Master
Realtids- och inbyggda system med tillämpningar mot maskininlärning	PhD
Satellitbaserad fjärranalys	Master
Servicerobotik	Master
Spatial statistik med bildanalys	Hybrid Master and PhD
Språkteknologi	Hybrid Master and PhD
Statistics: Data Mining and Visualization	Master
Statistik: Affärsanalys	Bachelor
Statistik: Deep learning och metoder för artificiell intelligens	Master
Strategisk kommunikation och digitala media	Bachelor
Strategisk kommunikation: AI, kognition och kultur	Bachelor
Strategisk kommunikation: Public Relations	Master
Studiecirkel i djupa neuralnät	PhD
Studiecirkel om Deep Reinforcement Learning	PhD
Tillämpad artificiell intelligens	Hybrid Master and PhD
Tillämpad maskininlärning	Hybrid Master and PhD
Tillämpad maskininlärning	PhD
Tillämpad maskininlärning I	PhD
Tillämpad maskininlärning III	PhD
Tillämpad robotteknik	Bachelor
Verksamhet och artificiell intelligens	Master

Courses across all case universities (excluding Lund)

Advanced Data Mining	Master	Linköping University
Advanced Machine Learning	Master	Linköping University
Advanced Machine Learning	Bachelor	Malmö University
AI & Rätten	Master	University of Gothenburg
AI and Ethics in Theory and Practice	Bachelor	Linköping University
AI för naturligt språk	Bachelor	Linköping University
AI-programmering 1	Bachelor	Uppsala University

AI-robotik	Master	Linköping University
Algoritmer för maskininlärning och slutledning	Master	Chalmers
Algoritmer för maskininlärning och slutledning	Master	University of Gothenburg
Artificial intelligence for data science	Master	Malmö University
Artificiell intelligens	Master	KTH
Artificiell intelligens	Bachelor	Linköping University
Artificiell intelligens	Bachelor	Malmö University
Artificiell intelligens	Master	Uppsala University
Artificiell intelligens	Master	Uppsala University
Artificiell intelligens	Bachelor	Stockholm University
Artificiell intelligens - principer och tekniker	Bachelor	Linköping University
Artificiell intelligens 3: Djup maskininlärning och autonomt beslutsfattande	Bachelor	University of Gothenburg
Artificiell intelligens för digitala spel	Bachelor	Malmö University
Artificiell intelligens för interaktiv media	Master	Linköping University
Artificiell intelligens för spelprogrammering 1	Bachelor	Uppsala University
Artificiell intelligens för spelprogrammering 2	Bachelor	Uppsala University
Artificiell intelligens i samhället	Master	KTH
Artificiell intelligens och autonoma system	Bachelor	Chalmers
Artificiell intelligens och maskininlärning	Master	Uppsala University
Artificiell intelligens och multiagentsystem	Master	KTH
Artificiell intelligens och tillämpningar	Bachelor	KTH
Artificiell intelligens: kognitiva system	Master	University of Gothenburg
Artificiella neurala nätverk	Master	Chalmers
Artificiella neurala nätverk	Master	University of Gothenburg
Artificiella neuronnät och djupa arkitekturer	Master	KTH
Automated Planning	Master	Linköping University
Autonomous Vehicles - Planning, Control, and Learning Systems	Master	Linköping University
Avancerad dataanalys	Master	University of Gothenburg
Avancerad maskininlärning	Master	Linköping University
Avancerad maskininlärning med neurala nätverk	Master	Chalmers
Avancerad maskininlärning med neurala nätverk	Master	University of Gothenburg
Avancerad probabilistisk maskininlärning	Master	Chalmers
Avancerad probabilistisk maskininlärning	Master	Uppsala University
Avancerad simulering och maskininlärning	Master	Chalmers
Avancerade maskininlärningsmetoder	Master	University of Gothenburg
Avancerade teman i maskininlärning	Master	Chalmers
Bayesian Learning	Master	Linköping University
Bayesiansk dataanalys och maskininlärning	Master	Chalmers
Bayesiansk dataanalys och maskininlärning	Master	University of Gothenburg
Beräkningsmetoder för stokastiska differentialekvationer och maskininlärning	Master	KTH
Beslutsfattande för autonoma system	Master	Chalmers
Big Data Analytics	Master	Linköping University
Big Data Analytics	Master	Linköping University
Big data analytics	Master	Uppsala University
Big data i biovetenskap	Master	Uppsala University
Big Data och framtidens beslutsfattande	Bachelor	University of Gothenburg
Big Data: Social Processes and Ethical Issues	Master	Linköping University
Big data: Sociala processer och etiska frågor	Master	Linköping University
Cognitive Science Introductory Course	Bachelor	Linköping University
Computer Vision	Master	Linköping University

Data Analytics	Bachelor	Uppsala University
Data Analytics for Smart Cities	Master	Linköping University
Data mining	Bachelor	Linköping University
Data Mining - Clustering and Association Analysis	Master	Linköping University
Datoriserad bildanalys II	Master	Uppsala University
Deep Learning	Master	Linköping University
Den artificiella intelligensens etik	Bachelor	Linköping University
Design av AI-system	Master	University of Gothenburg
Digital förvaltning och artificiell intelligens	Bachelor	University of Gothenburg
Digitala bildalstrande system	Master	Uppsala University
Distribuerad AI och Intelligenta Agenter	Master	KTH
Djup maskininlärning	Master	Chalmers
Djup maskininlärning	Master	University of Gothenburg
Djup maskininlärning för bildanalys	Master	Uppsala University
Djupa neuronnät	Master	KTH
Djupinlärning i Data Science	Master	KTH
Djupinlärning i Data Science	Master	Stockholm University
Djupinlärning, fortsättningskurs	Master	KTH
eHealth: Aims and Applications	Bachelor	Linköping University
eHealth: Digital Applications on Promoting Health and Preventing Disease	Master	Linköping University
Elements of AI, Part 2: Building AI	Bachelor	Linköping University
Engineering and Cognitive Psychology	Bachelor	Linköping University
Etik för artificiell intelligens och interaktiva autonoma system	Master	Linköping University
Grunderna i AI	Bachelor	Linköping University
Grunderna i tillämpad maskininlärning	Master	KTH
Humanoid Robotics	Master	University of Gothenburg
Hårdvaruarkitekturer för djupinlärning	Master	KTH
Image Processing and Analysis	Bachelor	Linköping University
Intelligent Virtual Agents and Social Robots	Master	Linköping University
Internet of Things	Master	Linköping University
Introduction to data science and AI	Bachelor	Chalmers
Introduction to Machine Learning	Master	Linköping University
Introduktion till artificiell intelligens	Bachelor	Chalmers
Introduktion till Data science och AI	Bachelor	University of Gothenburg
Introduktion till digital humaniora	Master	University of Gothenburg
Introduktion till djup maskininlärning och förstärkningsinlärning	Bachelor	University of Gothenburg
Introduktion till maskininlärning	Bachelor	Stockholm University
Introduktion till maskininlärning: Naturliga beräkningsmetoder	Master	Uppsala University
Introduktion till programmering i Python och artificiell intelligens	Bachelor	University of Gothenburg
Kognitiv teknologi och artificiell intelligens	Bachelor	Linköping University
Kursplan för AI och filosofi	Bachelor	Uppsala University
Logik i datavetenskap och artificiell intelligens Logic in Computer Science and Artificial Intelligence	Master	Stockholm University
Lärande maskiner	Master	KTH
Maskininlärning	Master	University of Gothenburg
Maskininlärning	Master	KTH
Maskininlärning	Bachelor	Linköping University
Maskininlärning	Master	Linköping University
Maskininlärning	Master	Stockholm University
Maskininlärning	Master	Stockholm University

Maskininlärning av dynamiska system med systemidentifiering	Master	Chalmers
Maskininlärning för fysiker och astronomer Machine Learning for Physicists and Astronomers	Master	Stockholm University
Maskininlärning för medieteknik	Bachelor	KTH
Maskininlärning för sociala medier	Master	Linköping University
Maskininlärning för språkteknologi	Master	Chalmers
Maskininlärning för språkteknologi	Master	University of Gothenburg
Maskininlärning för statistisk datalingvistik: inledning	Master	University of Gothenburg
Maskininlärning inom språkteknologi	Master	Uppsala University
Maskininlärning och dataanalys	Master	KTH
Maskininlärning, avancerad kurs	Master	KTH
Maskininlärning, Big Data och artificiell intelligens	Master	Uppsala University
Medicinsk bildanalys och rekonstruktion i 3D	Master	KTH
Modelling and Learning for Dynamical Systems	Master	Linköping University
Multiple Regression and Time Series Analysis	Master	Linköping University
Multiple Regression and Time Series Analysis	Bachelor	Linköping University
Multiple Regression and Time Series Analysis	Bachelor	Linköping University
Mönsterigenkänning och maskininlärning	Master	KTH
Naturliga beräkningsmetoder för maskininlärning	Master	Uppsala University
Neural Networks and Learning System	Master	Linköping University
Neural Networks and Learning Systems	Master	Linköping University
Organisational Development and Digitalization	Bachelor	Linköping University
Planning for a Sustainable Information Society	Master	Linköping University
Probability Theory and Bayesian Networks	Master	Linköping University
Programsammanhållande kurs i maskininlärning	Master	KTH
Robotteknologi	Master	Uppsala University
Samhällets digitalisering: Forskningsfronten	Bachelor	University of Gothenburg
Scientific Visualization	Master	Linköping University
Scientific Visualization	Master	Linköping University
Skalbar maskininlärning och djupinlärning	Master	KTH
Smart Cities	Master	Linköping University
Social robotik och människa-robotinteraktion	Master	Uppsala University
Spelmotorarkitektur	Master	University of Gothenburg
Sports Analytics	Master	Linköping University
Språkteknologi med introduktion till maskininlärning	Bachelor	KTH
Statistical Modelling with Regression Methods	Master	Linköping University
Statistik och maskininlärning i högre dimensioner	Master	Chalmers
Statistisk inferens och maskininlärning	Bachelor	Uppsala University
Statistisk maskininlärning	Master	KTH
Statistisk maskininlärning	Master	Uppsala University
Statistisk oövervakad inlärning	Master	Stockholm University
Statistisk slutledning för stora datamängder	Master	University of Gothenburg
Teknologi, politik, samhälle	Master	University of Gothenburg
The digitization of society	Bachelor	Linköping University
Tillämpad maskininlärning	Master	Chalmers
Tillämpad maskininlärning	Master	University of Gothenburg
Tillämpad maskininlärning och datautvinning	Bachelor	KTH
Tillämpad maskininlärning och datautvinning för prestationsanalys	Master	KTH
Time Series and Sequence Learning	Master	Linköping University