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Artificial General Intelligence - a systematic mapping study

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Abstract: In this thesis, a systematic mapping study is performed on the field of artificial general intelligence. The goal of the study is to gain insight about the recent developments in the study field. This includes the focus points of the current reserch, possible research gaps, and how the research itself is conducted. TODO: more accurate, proper abstract

Keywords: Master's Theses, AGI, AI, artificial intelligence, systematic literature mapping, mapping study

Suomenkielinen tiivistelmä:

Tässä suunnitelmassa käydään läpi pro gradu -tutkielman mahdollista aihetta ja tutkimustapaa. TODO: translate when abstract done

Avainsanat: Pro Gradu,tutkielma, AI, tekoäly

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1 Introduction

The thesis will be a systematic research mapping on the field of Artificial General Intelligence (AGI). The goal of the thesis is to identify the themes and subfields of AGI research in recent years, what is being researched recently, and what kind of gaps exist on the field. For a while the AGI field was not so active and the more specific approaches, 'narrow AI', grew in popularity. Recently, however, the wider, more general artificial intelligence has been regaining interest. This kind of mapping study would be needed as the research field is complex and there is no clear presentation of the current trends and focal points. Creating this king of overview would be a valuable asset for future research, as it would enable focusing the research on areas less ventured. Furthermore, if an interesting subtopic comes up during the process of mapping, more focus may be directed towards that in form of more traditional systematic literature review. This option is left for further consideration.

What each chapter is about, how the thesis is structured etc.

2 Artificial General Intelligence

TODO: Here some chapter introducing text

2.1 History of Artificial Intelligence

Even though the idea of autonomous machinery has been around since the ancient Greek (), AI's origins are set around in the 1940s. At the time, American science fiction author Isaac Asimov wrote numerous novels and short stories about conscious robots and technology's relation to humankind. His work has inspired countless people in the field's of AI and computer science since then (Haenlein and Kaplan July 2019). Also in the 1940s, mathematician Alan Turing's work on Britain's code breaking efforts lead to the creation of first electromechanical computer, The Bombe (Haenlein and Kaplan July 2019). Turing later gave lectures and wrote an article titled *"Computing Machinery and Intelligence"* (1950), in which he presented several ideas later prevalent in AI field, including the "Imitation game", a test to measure the intelligence of a machine (Russell and Norvig 2009). This later became well known as the Turing test.

The term Artificial Intelligence was coined in 1956 during a two-month workshop *Darthmouth Summer Research Project on Artificial Intelligence*, organized by John McCarthy and Marvin Minsky (Haenlein and Kaplan July 2019). The participants of the workshop would later become the most prominent figures of AI research. During DSRPAI two researchers, Allen Newell and Herbert Simon presented Logic Theorist, their existing reasoning program, capable of proving multiple mathematical theorems (Russell and Norvig 2009). Based on this work the two later created General Problem Solver, GPS, which could solve simple puzzles like Towers of Hanoi using human like recursive approach (Newell, Shaw, and Simon 1959). The early days of AI research produced many similar results in different areas. IBM's Arthur Samuel created AI programs that learned to play checkers at a strong amateur level (Russell and Norvig 2009). John McCarthy's 1958 paper titled "Programs with common sense", describes Advice Taker, a complete but hypothetical AI system with general knowledge about the world and deductive processes to manipulate it. The paper is still thought to be relevant today. McCarthy's system was able to acquire new skills in previously unknown areas without being reprogrammed.

During these years also work on the neural networks started to gain interest. The initial work of McCulloch and Pitts (1943), later demonstrated by Hebb (Russell and Norvig 2009), showed that a neural network is capable of learning. In 1960s Rosenblatt's work on perceptrons and Widrow and Hoff's LMS algorithm were some of the biggest advances in the area (Widrow and Lehr 1995). The next great discovery that would propel the neural networks into the focal point of AI research would happen in the mid-1980s when the backpropagation algorithm originally presented by Bryson and Ho in 1969 was rediscovered by multiple independent groups (Russell and Norvig 2009). Backpropagation is one of the most widely used algorithms for training neural networks these days for its relative power and simplicity (Rumelhart et al. 1995).

History of artificial intelligence contains occasional periods of reduced interest and funding. These so called "AI winters" are a result of high expectations collapsing under criticism. First period that can be considered an AI winter started in the 1970s, and Russell and Norvig (2009) present the following possible reasons for it: Firstly, the early programs knew nothing about their context, and solved the problems via syntactic manipulations. This was especially apparent on machine translation projects. As a language cannot be fully understood without knowing the full context of the sentences and other nuances of the language, accurate translation proved to be a difficult task. Failed translation efforts lead to funding cuts in the US. Second difficulty pointed out by (Russell and Norvig 2009) was the sheer complexity of the target problems. As the early AI programs were focused on simple tasks, finding a solution by trial and error was possible in practice. But as the problems became more complex, "combinatorial explosion" issue became more apparent. The issue was also discussed in British scientist James Lighthill's report on the state of the AI (1973). The report is considered to be one of the main reasons why the British government decided to cut all AI funding in all but two universities. Lastly, the limitations of the data structures used in AI field, such as perceptrons, restricted the capabilities of the solutions. According to Russell and Norvig (2009) this lead to funding cuts also in the neural network research.

During and after the first AI winter, there was a considerable amount of research relating to expert systems (Russell and Norvig 2009). These systems perform their tasks in a way similar to human experts in the specific, narrow domain, relying on a knowledge encoded into a set of rules (Myers 1986). This style of AI research was inspired by the success of DENDRAL (Buchanan, Feigenbaum, and Lederberg 1968), a system developed at Stanford by Ed Feigenbaum, Bruce Buchanan and Joshua Lederberg. DENDRAL's purpose was to use data from mass spectrometer to infer the structure of a given molecule. MYCIN, developed in the 1970s (Shortliffe et al. 1975), incorporated domain knowledge acquired through expert interviews, with the uncertainty of medical evaluation taken into account via certainty factors (Russell and Norvig 2009).

Expert systems gained commercial interest, leading to increased research and adoption in the industry. Government investments in Japan lead to increased funding in United States and Britain, leading to an AI boom in the 1980s (Russell and Norvig 2009). After the boom, at the end of the 1980s, the second AI winter arrived. Participation in AI conferences dropped, several of the new AI companies met their end, as did the AI research divisions in larger hardware and software companies (Nilsson 2009). The imminent burst of the bubble was foreseen by several leading researchers, but their warnings didn't have considerable effect (Nilsson 2009).

According to Russell and Norvig (2009), around this time the AI field started to adopt the scientific method. This means the earlier ways of proposing completely new theories based on vague evidence or oversimplified examples have been replaced by basis on existing theories, repeatable experiments, and real-world examples. This newly discovered open-mindedness then lead to a complete new ways of looking at the AI research. AI solutions based on existing theories, such as speech recognition based on hidden Markov models, enables the researchers to build on the rigorous mathematical theory behind it (Russell and Norvig 2009). Work of Judea Pearl (1988) and Peter Cheeceman (1985) on the probabilistic reasoning lead to it being accepted back into the AI field. Later Pearl's Bayesian networks have been used to handle uncertainty in AI problems. They are graphical models that join probabilistic information and dependencies to events, enabling inference using probabilistic methods (Goertzel and Pennachin 2007).

In the 21st century artificial intelligence research has been steadily growing. According to

(Liu et al. 2018), not only has the amount of publications in the field been increasing, but also the collaboration between researchers. The study also deduces that that AI has become more open-minded and popular, as the rate of self-references is reducing. One reason for the rising popularity on the field is the success that narrow AI solutions have presented in multitude of problems. For example, in classical game of Go, program called AlphaGo developed by Google-owned DeepMind, defeated the world champion Lee Sedol in 2015 (Silver et al. 2016). Due to Go's computationally complex nature this was a impressive feat previously thought impossible. Later DeepMind developed even more advanced versions of AlphaGo, called AlphaGo Zero, and generalized AlphaZero, which could even play Shogi and Chess on superhuman level (Silver et al. 2018).

Recent years majority of the field has been focusing on the narrow AI approaches (Goertzel and Pennachin 2007). However, the interest in the classical, strong AI has also been increasing. This can be seen in the publications from many influential AI researchers. Authors like John McCarthy (2007), Nils Nilsson (2005) and Marvin Minsky (2007) have voiced their opinions that efforts to create a more general AI should be pursued. There are several terms used regarding these efforts. **Human-level Artificial Intelligence** (HLAI) aims to reach "human-level intelligence" and common sense, a goal that according to Marvin Minsky (2004) can be reached by not using any single method, but a combination of different resources and methods. Similar term is **Artificial General Intelligence** (AGI) presented by Ben Goertzel and Casio Pennachin (2007). The goal of AGI is similar to HLAI, to create an AI system that can express general intelligence instead of being locked into a single domain. On the next chapter this general approach is presented in more detail, as it is the focus of this thesis.

2.2 Definition

In order to be able to define AGI, or artificial intelligence in general, one must first consider the definitions of intelligence in general. The exists many different definitions, in many different branches of science. Legg and Hutter (2007) list over 60 definitions collected from various academic sources. These include, for example, *"the general mental ability involved in calculating, reasoning, perceiving relationships and analogies, learning quickly, storing* *and retrieving information,using language fluently, classifying, generalizing, and adjusting to new situations."* (Columbia Encyclopedia, sixth edition, 2006), *"that facet of mind underlying our capacity to think, to solve novel problems, to reason and to have knowledge of the world"* (Anderson 2006), and *"Intelligence is the ability for an information processing system to adapt to its environment with insufficient knowledge and resources."* (Wang 1995). Based on the aforementioned collection of definitions, Legg and Hutter (2007) have formed the following definition: *"Intelligence measures an agent's ability to achieve goals in a wide range of environments"*. This gives us a single definition which encompasses the common traits in intelligence definitions.

Artificial General Intelligence, sometimes referred as "strong ai", according to Goertzel and Pennachin (2007) means *"AI systems that possess a reasonable degree of self-understanding and autonomous self-control, and have the ability to solve a variety of complex problems in a variety of contexts, and to learn to solve new problems that they didn't know about at the time of their creation."*. It can be seen that an agent fulfilling this definition also possesses the intelligence defined in the previous chapter. In this thesis terms artificial general intelligence and human-level artificial intelligence are treated as synonyms, as they pursue more or less the same goal of general intelligence. Goertzel and Pennachin (2007) suggest that the term AGI is more fitting to the area than HLAI as it human-like approaches are not necessarily used.

The reason general intelligence is specified instead of plain intelligence is that there is a need to differentiate it from the domain specific artificial intelligence, also known as "narrow AI" or "weak AI", that has become prevalent in AI research in recent past. Terms strong AI and weak AI were coined by John Searle in 1980 (John et al. 1980). Narrow AI means smart solutions that may learn and improve their performance through training, but they are only focused on specific type of problems in a specific context. Examples of such AI include chess engines, autonomous vehicles, and natural language processing. These solutions may outperform human capabilities, but only in their limited tasks. When presented a problem outside their domain, they usually perform poorly. As the above definition by Goertzel and Pennachin describes, AGI is able to function on different context and tasks without separate human intervention and reconfiguration.

As The AGI community is diverse and there are multitude of opinions on the best approaches and the goals that should be pursued in the research, several possible roadmaps have been presented in an attempt to create a common basis for the discussion and research of human-level artificial general intelligence. In (Adams et al. March 2012) a high level roadmap with AGI's initial required capabilities and scenario-based milestones is suggested, building on previous work and workshops organized in 2008 and 2009. Presented scenarios can be used to measure the progress and capabilities of AGI restricting the progress of different approaches to a single test situation (Adams et al. March 2012). More concrete example is provided by Ben Goertzel and Gino Yu, who outline creation of a AGI-oriented cognitive architecture based on existing CogPrime architecture (Goertzel and Yu 2014). A simultaneous development of multiple AGI-style applications is suggested to maintain the generality of intelligence. CogPrime is implemented with OpenCog framework, developed by OpenCog Foundation and AI researcher Ben Goertzel. OpenCog is an attempt to create an open source framework for artificial general intelligence (*The Open Cognition Project;* Goertzel 2012).

TODO: Add something like: One motivation behind this thesis is to find out if these roadmaps and "common ground" have actually lead to anything concrete, or has their effort been for nothing.

3 Systematic literature mapping process

Systematic literature mapping is a secondary study method that helps to identify the focal points and research gaps in the subject area, providing an overview of previous research (Petersen et al. 2008). It is also known as systematic mapping study or scoping study (Kitchenham and Charters 2007). This chapter introduces the mapping method, describing each phase of the mapping process. The key differences with a more common study method, systematic literature review (SLR) are also presented, as well as the reasoning behind this method choice.

3.1 Research method description

Systematic mapping is a common research method used in fields such as evidence-based medicine, but have until recently been rare in software engineering (Petersen et al. 2008). Kitchenham, Dyba, and Jorgensen (2004) suggested that adopting evidence-based approach to software engineering research might benefit the industry by ensuring approaches used are backed by evidence. Aggregating evidence is done by systematic literature reviews and similar secondary studies, such as mapping studies (Kitchenham et al. 2010). As researcher bias is one the weak points of secondary studies, adhering to strict protocol and guidelines is required to minimize it (Brereton et al. 2007).

The systematic literature mapping in this thesis is following the method guidelines presented by Petersen et al (2008), later updated in by Petersen, Vakkalanka and Kuzniarz (2015). The mapping process overview can be seen in figure 1. It consists of five separate phases: **definition of research questions, conducting search, screening of papers, keywording, and data extraction and mapping.** Each phase produces a subresult to be used in the next one. This process results in a systematic map of the area. This can and should be further visualized using for example bubble graphs, as it is a powerful way to achieve a quick overview of the field. (Petersen et al. 2008). This also enables easier recognition of research gaps and focus points in the target area.

The process begins by defining focused research questions that are aligned with the goal

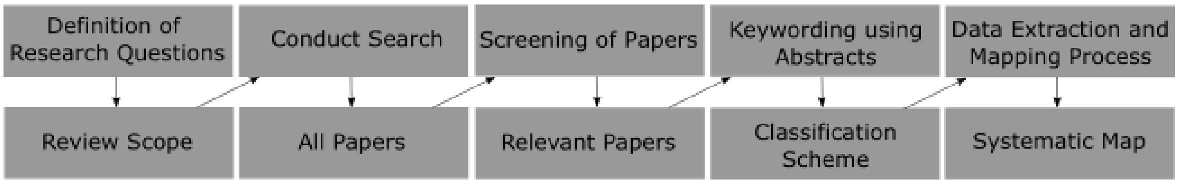

Figure 1. Process model (Petersen et al. 2008)

of the study. The goal of the study often is to create a general overview of the research area, and to identify the type and quantity of research (Petersen et al. 2008). Unlike in more focused systematic literature reviews, the research questions of mapping studies are less focused and cover a broader scope (Kitchenham et al. 2010). For example, possible research questions on studies could be: *"Which are the most investigated quality aspects of the software requirements specifications techniques?"* (Condori-Fernandez et al. 2009) or *"What efforts have been reported in literature for Software Engineering curriculum design, implementation, assessment and management?"* (Qadir and Usman 2011). These topic-oriented questions are often combined with research questions regarding the meta-level information, such as publication year, venue, and research methods (Petersen, Vakkalanka, and Kuzniarz 2015).

The next phase of the mapping is the initial material search, which can be conducted multiple ways. Search strings can be formulated from the research questions, and used on academic databases and search engines (Petersen et al. 2008). For example, databases such as IEEE Explore and ACM, as well as aggregators like Google Scholar can be utilized. As the search phrases should be research question driven, following a criteria such as PICO might prove to be helpful, as suggested by Kitchenham and Charters (2007). PICO (Population, Intervention, Comparison, Outcomes) provides an frame to consider research questions' elements and identify keywords. As the goal is to achieve broad overview of the research, study outcomes are not taken into account, as this could result in a biased results (Petersen et al. 2008). The search can also be conducted manually on specific journals and conference proceedings that cover the target area (Petersen et al. 2008). This approach is used in this thesis, as it enables targeting specific reputable and well-known publication venues. TODO: Update when search method is clear.

After the initial material has been gathered, it is further refined by excluding papers not relevant to answering the research questions (Petersen et al. 2008). Separate criteria for both inclusion and exclusion is used to find the papers fit for further analysis. According to Petersen, Vakkalanka and Kuzniarz (2015), the criteria may refer to relevance to the topic, publication venue, time period, language restrictions, and evaluation requirements. Considering evaluation requirements should be avoided with systematic maps as it might limit recent trends. Once the criteria is decided, it is applied to the titles and abstracts of the articles (Petersen, Vakkalanka, and Kuzniarz 2015). In case of unclear or poor quality abstracts also the introduction and conclusion sections of the article may be studied (Petersen et al. 2008). As no full-text reading is required, screening of papers can be performed rapidly.

Once the final set of papers is narrowed down and determined, keywording is performed. As described by Peterson (2008), The keywording process starts by first by analyzing the research papers' abstracts by searching possible frequent keywords and prevalent concepts from them. The keywords of each paper are then combined together to achieve a more general set of concepts. On some cases having a more detailed inspection of the article might be required (Petersen et al. 2008; Petersen, Vakkalanka, and Kuzniarz 2015). After the final set of keywords is chosen, they are clustered into categories representing the article population (Petersen et al. 2008). This emergent classification schema can then be used in the data extraction phase.

Different research facets can be used in the classification. For example in addition to the topical scheme emerging from the keywords, a topic-independent facet reflecting the research approach can be used. One example of the latter is the classification of research approaches by Wieringa et. al (2006). Wieringa's classification categorizes scientific papers into six categories such as validation research, solution proposals, and opinion papers. Using existing topic-independent categorization also enables the comparison of different research fields (Petersen, Vakkalanka, and Kuzniarz 2015).

In the final phase of the mapping process, the data extraction is performed by sorting the papers into the classification schemes present (Petersen et al. 2008). The schema may evolve during the data extraction process, changing the categories to match the article population more accurately (Petersen, Vakkalanka, and Kuzniarz 2015). The categorization based on the chosen facets results in a frequency table, i.e. the mapping, with can then be presented with via visualization and summary statistics. Visualization using for example bubble plots is preferred, as it is a powerful way to represent the information and map of the field (Petersen et al. 2008).

3.2 Differences with systematic literature reviews

Because the systematic literature mapping as a study methods is less known in the field of software engineering, the typical differences between it and more common secondary study method, systematic literature review, is presented here. There is many common factors in both of the methods, and as Kitchenham et al. (Kitchenham et al. 2010) state, *"the distinction between mapping studies and conventional SLRs can be somewhat fuzzy"*. They also present a view that mapping studies are just a different type of systematic literature review.

Similar to other secondary study methods, mapping study aims to summarize and present the research performed in the past. Whereas systematic review focuses on very narrow research questions, mapping study usually has multiple broader questions(Kitchenham et al. 2010). Difference in scope breadth can also be seen in the search strings, as the initial material search for mapping is likely to return large number of studies (Kitchenham and Charters 2007; Petersen et al. 2008). Mappings are usually conducted to achieve an overview of the research area, and therefore the depth of the studies is not as great as in the SLRs. The mapping focuses more on the thematic analysis of the articles instead of in-depth analysis of their results or gathering empirical evidence based on their results, which is often the goal of an traditional SLR (Petersen et al. 2008). Therefore the quality of the objects of study is not relevant, unless the quality itself is the aspect to be investigated.

Since both methods have their strengths and weaknesses, using them complementarily can be an effective combination. As suggested by Petersen et. al (2008) and Kitchenham et al. (Kitchenham et al. 2010), good approach is to first get an overview of the research area with systematic map, and then applying conventional literature review to a specific focus area. Results of the mapping can provide information on the quantity of available evidence, which can help targeting the follow-up SLRs more precisely.

3.3 Background/reasoning behind method choice

The following text is very raw, will be edited properly later

- Should reasoning for this particular method and these particular guidelines be here? Esp. (Petersen, Vakkalanka, and Kuzniarz 2015) which presents other guidelines and their usage should be useful, as well as kitchenham's studies on literature reviews. These are also most common ones.

larger fields can be structured

Presenting background on the mapping studies in IT as part of reasoning?

As a thesis topic, Artificial General Intelligence is a challenging and a wide area. By focusing on the AGI research articles as an object of study, useful research can be performed without requiring too much prior knowledge and expertise on the topic from the author. The reason behind the choice of systematic literature mapping is that it fits specifically well on creating overviews of the study area. Due to the complexity of the area, it is difficult to enter as a beginner. As suggested by (**x**), systematic mapping of the field can help understanding it better, and to act as an entry point to it. It can also be useful in introducing it to people unfamiliar with the field, both in academia and in business side. It is also a topic that is known of it's boom seasons etc., so seeing the trends and state of the research can be interesting, and mapping is a good way to achieve that. As there is no specific, focused research question, mapping is better choice than review.

Guideline choice: Common and popular, clear methodology, other guidelines taken into account in the update. Wieringa's classification is clear and covers necessary types without making categories too specific and thus increase the workload in the process. Other options mentioned here?

4 Conducting the literature mapping

- To ensure study is conducted with rigor, should it be documented and reported very carefully.

4.1 Research questions

The following research questions...

1. How much, and what type of research is done in the field of AGI?
2. Where is the AGI research focused on?
3. Has there been any major breakthroughs? TODO: This should be something else maybe, as study should avoid outcome evaluation
4. Where and when were the studies published?

4.2 Sources and databases used

- Journal listing and their date ranges etc.

- Why journals were chosen, information about them, reliability, area coverage, jufo rankings etc.

- search terms here or another section?

- table showing used search phrases?

High level and/or topical relevance make these the ideal candidates for the review.

Issues are looked only on years **2015-2019**

- **3 ARTIFICIAL INTELLIGENCE |** citescore 7.7 | Impact factor 6.628. Issues 218-277 = 59, articles in issue c. 10,

- **3 JOURNAL OF ARTIFICIAL INTELLIGENCE RESEARCH |** IF 1.8. Issues 52-66 = 14, articles in issue c.20

- **1 JOURNAL OF ARTIFICIAL GENERAL INTELLIGENCE**. Issues = 6, articles in issue c. 2

- **INTERNATIONAL CONFERENCE ON ARTIFICIAL GENERAL INTELLIGENCE**. Issues = 5, articles in issue c. 30. This conference seems to be surprisingly active and on topic.Not in JUFO rankings.

What about this? Has JUFO ranking. - **1 EUROPEAN SYMPOSIUM ON ARTIFICIAL NEURAL NETWORKS, COMPUTATIONAL INTELLIGENCE AND MACHINE LEARNING**. This would increase article load with 500+ articles, with a low number of relevant papers. So maybe? Maybe not, as paper amount with IJCAI is already massive.

==> In total, around 1000 articles concerning AI. Quick sampling shows the number actually relevant articles may still be very low. Should interval be lengthened or is this ok?

- **International joint conference on Artificial Intelligence** Massive amount of papers. Manual search not feasible.

What about performing search on journals?

4.3 conducting search

Search phrases are used on different databases, limiting the papers to amount possible to handle

Search can be also done by inspecting relevant journals (like here)

- evaluation of search: test set of known papers, possible here?

4.4 Criteria for inclusion, exclusion

Criteria is presented, and papers are further narrowed down.

4.5 Keywording

Papers are further analyzed, keywords are extracted from abstracts and text.

4.6 Data extraction and mapping

keywords are used to create a mapping, working iteratively. Papers are categorized based on the emergent mapping. What about existing categorizations, like Kitchenham? Probably should use multiple facets, like kitchenham, and the emergent schema.

4.7 Source material control

- How the papers were handled - How graphs etc. were made - Other meta level information - Excel, python, etc.

5 Results and analysis

The results of the thesis will be a clear overview of the recent research in the field of artificial general intelligence in form of classification data, visual graphs and further synthesis. As mentioned earlier, if an interesting topic presents itself during the process of mapping, it may be further examined in a more focused way, such as literature review. This will be considered at that time.

5.1 Validity threats?

- performed alone, researcher bias etc (multiple people not possible here), how rigor is achieved, repeatability,

Good source on reliability Wohlin et al. 2013

5.2 Results of literature mapping

- Graphs and other visualization, bubble graphs are useful. - Key topics should be described shortly?

5.3 Possible continuation research

- List of most prominent topics for further research

6 Conclusion

In this thesis, a systematic literature mapping was conducted on the field of artificial general intelligence. Results of the study showed that ....

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