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ANALOGY RETRIEVAL THROUGH TEXTUAL INFERENCE

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ABSTRACT

Analogy-making has been deemed one of the core cognitive mechanisms which play a role in human creative thinking activities such as design and art. Designers can make use of analogies in various stages of design including ideation, planning and evaluation. However, human analogy-making is limited by experience and reliance of human memory on superficial attributes rather than relational or causal structure during analogy retrieval. In this regard, different design-by-analogy tools have been developed to assist designers in analogical reasoning. Analogical reasoning tools can be viewed as either based on hand-coded structured knowledge or natural-language-based design-by-analogy tools. The former are naturally limited in extent and scope to that which was hand coded [1]. Alternatively, natural language analogical reasoning can leverage the abundantly available textual resources. Current text-based analogy research for design have relied on analogies between individual word meanings. This leaves open consideration of the relational structure of the language where the relational similarity of texts can indicate a significant analogy. In this article, we develop four computational models of analogy that capture relational structure of the text. This includes spatial representation of semantics, multi-level deep neural reasoning, graph matching based model and transformation-based model. The models are then combined together into an ensemble model to achieve acceptable level of analogical accuracy for the end-user. The underlying design-related knowledge upon which analogies were drawn includes engineering ontologies, function hierarchy and raw patent texts. Instantiating this analogical reasoning model in design concept analogy retrieval system, we show this approach can help retrieve meaningful analogies from the World Intellectual Property Organization (WIPO) patent repository. We demonstrate this for a particular design problem.

INTRODUCTION

Humans can be considered to attain knowledge and experience about objects, events and abstract concepts they don't know well from entities they are more familiar with. Analogical reasoning, the ability to perceive one situation as another at higher level of abstraction is deemed fundamental to the human cognitive process [2]. Analogical reasoning is argued to be not merely an isolated human capability but a key cognitive process which differentiates humans from other intelligent species. Clear relationships are observed between analogy-making and cognitive processes such as linguistics, long-term memory retrieval, and categorization[3,4]. Analogy is also known to play a significant role in creative fields like design, art and science [5].

Analogical reasoning is also used extensively and effectively by professional designers [6]. Expert engineers often use cross-domain analogies in their concept generation [5,7] and close-domain analogies in process planning, cost estimation, and evaluation of concepts for new products [6]. Yet, a designer's mental repository of analogies is limited by their exposure to similar cases and humans memory tend to retrieve analogies based on their resemblance with a current problem or solution instance, rather than relational similarity in higher level of abstraction. Given these limitations, developing computer tools to retrieve functionally similar concepts from large repositories of design knowledge could be helpful to augment a designers' natural capability in analogy-making.

Current tools available for design by analogy can be classified as either based on hand-coded structured representations or natural language. Hand-coding structured representations requires considerable human effort which makes extent and scope of knowledge covered by such systems considerably limited [8]. Conversely, textual information are abundantly available as large number of design-related information are documented in form of patents, websites, technical articles, scientific publications and etc. Accordingly a considerable number of design-by-analogy tools have been developed to leverage available textual resources. To date, methodologies proposed for retrieving analogies from texts have been based on the meaning of individual words and relations without considering the text's overall sentence structures. A difficulty has been that analogy between two sentences not only depends on ontological relationships among their entities but also on relational similarity of their structure. In this work, we purpose a new model of design analogy which captures relational structure of text describing the design by incorporating analogical textual inference.

Textual analogical inference considers the sentence structure. For example sentence structure analogical reasoning would detect an analogy between a pair of sentences such as "*A valve controls the flow rate through changing the width of the pipe*" and "*A transistor regulates the current by adjusting the resistance between collector and emitter*." Notice the words and their context are not the same, rather the sentence structure itself indicates the analogy.
We use this approach for design purposes by considering textual descriptions of novel design concepts. We retrieve analogies from WIPO patent repository. We make use of four available analogical textual inference models: spatial model of textual semantics, transformation-rule based, and structural alignment based and multi-level deep neural reasoning model. These models will be discussed at length.

Accuracies of individual analogy text recognition models proved insufficient to generate meaningful design results for end-users. Therefore we combined the models together into an ensemble model which demonstrated much higher accuracy. Our approach thereby benefits from the various resources of design knowledge found in raw patent texts, a set of engineering ontologies[9–11] and function hierarchy [12].

The structure of this paper is as follows, first, models of analogy-making in humans are discussed and in particular, computational models of analogy-making. Then the state of the art in design-by-analogy research for design are reviewed and categorized according to their knowledge representation. Next, our text-based models of analogy recognition are discussed. Our design analogy retrieval system based on the developed analogy recognition models. Finally, our design retrieval system is used to find useful design concepts for a particular case-study and the results obtained from the system are compared with using Google/Patents as commonly used by designers to explore patents.

LITERATURE REVIEW

Analogy making: a core cognitive mechanism

Hofstadter [13] describes analogy as the process of understanding multiple "conceptual skeletons" at the correct layer of abstraction and retrieving them based on their "ports of access." These ports represent the handles through which a concept is retrievable later. Hall [14] presented a four-phase model of the analogical reasoning process, which recognizes the distinct phases of *retrieval, mapping, induction* and *abstraction*. While other researchers describe slightly different subdivisions of this process, there is broad agreement on these phases. Analogy making begins with retrieval or recognition of an analogue or analogues on the basis of the given target description, proceeds with mapping relational structure of source and target to evaluate level of alignment between the two and determine 'what goes with what' and and then making inferences about the target based on its structural resemblance with the source. Inferences are made upon the intuition that if two things are similar in some aspects in a consistent way, they could be similar in other aspects as well. Final step is memorizing the outcome of the inference as an abstraction, in form of a schema or other rule-like structures, Besides these four well-accepted steps, encoding, dynamic representation-building mechanisms and parallel sub-process interaction are also argued to be cognitive processes essential for analogical reasoning [15]. It is also suggested that representations of source and target might be modified to allow better alignment based on their initial match [16].

Some theories of analogy are mainly on the basis of cognitive architecture such as the production system architecture [17] and realize analogy in terms of the elements of such architectures, like production rules, short-term memory, and focus of attention. Other accounts of analogy suggest general-purpose mechanisms which are largely independent of task or domain, problem size or problem solving time, knowledge content, and knowledge representation modality [18].

French [19] classifies computational models of analogy into three major classes according to their primary architectures: symbolic models are largely influenced by the symbolic paradigm in artificial intelligence and built upon high-level symbolic representations of problems, logic and search;

connectionist models adopt the framework of the connectionist networks; and hybrid models that combine elements of connectionist and symbolic models.

Symbolic systems are generally well equipped to model relational structures involving situations represented as objects and relations between objects. For this reason, these models held the high ground for many years in the computational modelling of analogy-making. Alongside symbolic models, connectionist models of analogy-making have taken their place owing to generality of their representation. Distributed connectionist representations provide a natural internal measure of similarity to allow the system to handle a problem with similar, but not identical, relationships more easily than symbolic models. Hybrid models share features of both connectionist and symbolic models. Hybrid systems are consisted of neurons which allows for symbolic interpretation or interactions.

Different theories of analogy give different levels of significance to deep or schematic information compared to surface or semantic content in analogical reasoning process. Structure mapping theory [18] and pragmatic-schema theory [20] put considerable importance to deep information during mapping. Conversely, theories like exemplar-analogy takes all aspects of surface features into consideration in the mapping process.

Design by Analogy: A key tool in designer's toolbox

Design by analogy is used extensively to generate creative solutions for new problems [7]. Analogy can be used in problem solving in different ways: transformational analogy aligns the structure of a previous solution to the new problem, while derivational analogy applies the source problem-solving strategy to the process of solving of the new problem. Using analogies in either form has been a significant driving force in evolution of technology and creation of new products [21]. Qian and Gero [22] describe analogy as sharing similar function or behavior but not necessarily having similar structures. For example, a hydrofoil can be viewed as an analogue for airplane wing as it generates lift using flow over it surface in a similar way. Dissimilarity between air flow and water flow or other potential surface details does not invalidate the analogy.

Analogies can be used for understanding and identifying the problem, blockbusting and reducing fixation when solving the problem, and communicating the problem or solutions to other designers in the concept development phase [5]. Usage of design-by-analogy is not limited to early stage conceptual design and analogies with existing designs can be used in other phases of the design process, including process planning, cost estimation, and evaluation of concepts [23]. Several researchers have investigated the content of analogies in real-world engineering design [24]. They found that problem-identifying analogies were mainly within domains, explanatory analogies were primarily between domains, and problem-solving analogies were a mixture of within and between domain analogies. Design-by-analogy is also shown to be potentially implementable as a systematic organizational concept generation mechanism to make breakthrough innovations in organization scale [5]. Analogy can be applied for problem solving even when the problem solver is not fully aware of [4]. Engineers often take ideas from previously experienced products without even knowing that what ideas are inspired by [25,26]. So investigation that rely on designers self-reports of using analogy are tend to underestimate important impacts of analogy [27].

As a human-based design methodology, design-by-analogy requires understanding of how people use design by analogy and what we can do to guide or assist them to improve the process. There has been important number of experiments to make our understanding deeper on role of analogies in design process. Previous research has been shown that representation of concepts in memory plays a crucial role in analogy retrieval. Retrieval will be facilitated, if source and target of analogy share key features, attributable to the principle of encoding specificity [28]. This principle states that memories are effectively retrieved when context during retrieval is similar as context while encoding. Context is defined as representation of information, attribute similarities along-side any external factors such emotional factors and physical location. This helps human brain economizing its cognitive resources but at the same time posits a limitation on broadness of retrievable information. Attribute similarities are in particular shown to have a significant role in retrieval of analogies [29]. Paradoxically, analogies are more likely to result into novel ideas when target and source domains are superficially different[30]. Positive correlation has been observed between number of far-field analogues used by designers and originality of proposed solutions as rated by potential customers [31], surface dissimilar design example are found to be positive effect on novelty of ideas generated and surface similar examples are found to have negative effect on variety of idea [32].

There also has been a great deal of interest in the roles of analogy and expertise in problem solving. A common finding in both novices and experts is analogies are helpful in solving problems [33], Experts are found to use considerably more analogies than novices [7,34]. experts are more proficient in using analogies and are more capable of retrieving analogies from their memories, experts also tend to be able of distinguishing the causal structure of products, and not distracted by surface attributes.[36, 37]. This dichotomy is attributable to the fact that experts see deeper, logical structure of situations while those without domain knowledge are mostly know of only the superficial features [36].

Both novices and experts have shown improvement in problem solving when they have been provided with visual analogies[7], but this improvement has shown to be more significant for novices compared to experts. Experts also found use analogies differently, while novices are more likely to use case-driven analogies where new solutions have been developed specifically based on a certain example, experts tend to use schema-driven analogies that a more general conclusion is built upon multiple examples [37]. This is probably due to the fact that it is easier for experts to retrieve relevant information when needed and map concepts from far domains [38].

Concept of abstraction is intertwined with analogy, two analogue concepts can be viewed the same in particular level of abstraction, In general, abstraction refers to the specificity with which those concepts are modelled, a single highly abstract relationship involves an ensemble of many lower order relationships consisting of sizes, distances, and physical laws. That is, abstraction is argued to be a significant element for successful transfer of analogy [39], Instead of mapping a large ensemble involving many relationships, a designer can rely on a fewer abstract relationships. Functional diagrams, graph grammars, black-boxes and band-graphs, physical principles, working geometry and working motion are few of various forms of abstractions suggested in design literature. Many of design-by-analogy tools are working by transforming the problem into higher level of abstraction, finding solutions of other problems that fits the abstract form of the problem and adapting it to the problem in hand.

Design by Analogy Tools: Help filling experiential gap between novice and expert designers

Variety of factors may limit ability of designers, particularly novices, in utilizing analogies in creative problem solving. Novice designers may fail in encoding their experiences with appropriate "ports of access" in such a way that facilitates retrieval process. They may find it difficult to focus on causal relationships at a level higher of abstraction and remain fixated to attributional and structural similarity during retrieval of analogies. They might have inadequate exposure to suitable analogies. Even once a potentially useful source of analogy retrieved from their memory, selecting appropriate features to map from the source of analogy to the target problem is not a straightforward task [40,41]. Such limitations are not inclusive to novices and might be restrictive even for experts while looking outside their scope of expertise for making cross-domain analogies. It would be helpful to have tools that assist novice designers to represent and process of information similar to experts to minimize the effects of the experiential gap between novices and experts [42].

Computer aided design-by-analogy tools can potentially augment designers in fore-mentioned challenges by providing means to construct better structured representations, capturing causal relations among concepts at appropriate level of abstraction, retrieving information from large repositories of design knowledge and map them appropriately to the problem in hand. In following sections we introduce design-by-analogy tools developed based on two main categories according to the type of knowledge representation.

Tools based on Structured Knowledge

The Function-Behavior-Structure (FBS) model [43] is one of the most common approaches to represent product conceptual knowledge. In this model, design conceptual knowledge is represented in terms of Structure, behavior predicted from structure, function, expected behavior, and design description. In this representation design process is modelled as a translation from function to design description. Commencing with Structural mapping theory[18] and deploying it on FBS representation, Gero and Qian developed first computational tools to search between-domain design-by-analogy tool that explores systematic analogical mappings through causal links among structure and structure, and among structure and behavior.

Kritik, IDeAL, CADET, and DANE are other design-by-analogy tools that are built upon FBS representation of knowledge. In the late 1980's, Goel and his coworkers developed Kritik, one of the first case based design systems that automatically generated preliminary designs for physical systems through retrieving prior design stored in its repository. Each entry in repository is accompanied with a FBS that relates structure and function. In Kritik, FBS models guided the process of refining prior designs to meet new functions, by providing methods for design adaptation and verification, and helping retrieval and storage processes.

The IDeAL system is one of implementations of a schema based model for conceptual design. IDeAL makes use of FBS models for pattern finding, constraint analysis, and problem reformulation[44,45]. IDeAL makes use of design patterns for analogical transfer in design-by-analogy. Design patterns are transferred from source cases to target problems using model-based-analogy according a normative-theory of analogy-based design. For physical devices, they introduced a class of design patterns to specify generalized functional relations and abstract causal structures. While these patterns provide a content account of analogical transfer to some extent, model-based-analogy provides a process account of acquisition, access, and use of these patterns.

CADET[46] uses a simpler form of effects but an otherwise very similar type of graph for model representation. The goal of CADET was to enable the mechanical engineer to perform model-based adaptation of the past design. CADET leaves adaptation and evaluation tasks to the designer through an interactive interface. It provides designer with a repository of simple mechanical devices while each design contained a causal model of the system.

Design by Analogy to Nature Engine (DANE) is a design case repository containing structure behaviour–function models of natural and artificial systems [47]. Dane provides a framework to retrieve previous models based on name, subject, or verb in multimedia form and author new models into the library. Beside FBS, other knowledge representation models are also utilized in design-by-analogy tools. IDEA-INSPIRE [23] is a systematic search tool which helps ideation by providing designers with relevant stimuli from natural or artificial systems. The software has two separate databases for natural and artificial systems with around 700 motion descriptions. For each motion, the description including the media it occurs (land, water, air …), and the way it occurs (leaping, walking, crawling,) is provided in both natural language and computer understandable language. Designer are supposed to provide problem description to the software tool either in verb-noun-adjective/adverb or constructs of SAPPhIRE model of causality which is consisted of seven elementary constructs that enables system and state description: state-action-part-phenomenon-input-organ-effect, software then searches for relevant analogy within its entries and provide it to the user.

Tools based on Unstructured Knowledge

Second category of tools developed for design by analogy use textual representation of knowledge. Engineering-to-Biology Thesaurus developed by Nagel et al. [48], is another tool that associates terminology between engineering and biology for the identification of synonyms, strengthening ability of designers to utilize biological information. It is built around the terms of the Functional Basis and constitute of lists of correspondent terms produced by the BID lab search tool [49], Indian Institute of Science [50] and Oregon State University[51]. Hacco and Shu developed a biomimetic concept generation tool to systematically index biological phenomena[52] where keywords derived from functional requirements of the problem used to extract relevant entries from an introductory college textbook [52]. Chiu et al. [53] and Cheong et al. proposed and methodology to make effective analogy search possible in the abundantly available biological texts. The base of their approach is through matching functional basis terms with biologically meaningful keywords. The main challenge with their method is that fixation may occur on certain phrases on words in source biological descriptions which makes transferring biological information into target difficult.

Another notable example of text-based design-by-analogy tools is *WordTree* [54]. *WordTree* begins with identifying key problem descriptors from customer need descriptions, mission statements, function structures, and black box model. Key problem descriptors are single word action verbs describing the overall function of the device, critical or difficult to solve functions, and important customer needs. These lexicalized problem descriptions are then can be graphically represented in the form of graphs of words, this diagram is then extended through ontological relationships in *WordNet*. Potential domains and analogies is then identified based on key problem descriptors and used consequently to develop alternative domain specific and general problem statements. Finally, obtained analogies, patents, analogous domains and problem statements are used for concept generation in a group ideation session.

Text-based design-by-analogy tools developed so far are primarily based on word-to-word analogies and leave considering compositional and structural analogy between larger pieces of text open. Developing tools to retrieve analogies based on larger pieces of text could be worthwhile as sentences are more expressive than individual words and can contain more information about the problem. In this work, we develop four model for analogy based for textual representation of knowledge, these models are inspired by currently developed models for textual logical inference in natural language processing. This set of models includes spatial representation, graph matching, transformation-rule and neural reasoning based models. Concepts behind these models are analogous to different accounts of similarity based on mental representations in cognitive psychology namely, mental distance approach [55], Structure mapping theory [18] and Transformational model of similarity[56]. As accuracy of each of these models individually is not enough to obtain satisfactory end-results for the user, we combine their results using an ensemble model into a single score which then used to rank paragraphs in the patents.

As pointed out by Huhns [57], to develop design-by-analogy systems, an analytical similarity measure is needed. Higher success of design-by-analogy in the area of circuit design compared to mechanical design [57] is partly attributed to usage of quantitative similarity measures available in circuit design relative to mechanical design. Few different metrics have been purposed to address this concern, Murphy et al. [58] purposed a total relevancy score constituting of patent functional content metric and Query-Patent cosine similarity. McAdams and Wood [59] suggest a new metric which depends on both function and customer-need importance of the functions. Accuracy of these quantities measures become more important when we are selecting concepts out of large repository of designs. Our relevancy score system depends on similarity level between lexical entities on higher level of abstraction and relational similarity between the lexical entities describing two concepts.

ANALOGY RECOGNITION MODEL

Our models of analogy recognition are inspired by models of textual inference. Identifying logical consequences or textual entailment relations between two pieces of text is probably the most common task of textual inference in natural language processing. The task determines if the truth stated in one piece of text can be inferred from the truth expressed in the other, assigning a score representing the level of plausibility of such inference to a pair of text fragments. Models developed so far for textual entailment are either rule-based models relying on either a predefined set of rules to determine logical consequence between two sentences or statistical models such as neural networks that capture relationships between texts and their entailment relationship based on a set of training examples. Rule-based models benefit from pre-existing knowledge available in a set of knowledge bases, whereas for neural networks this knowledge is attained by automatically learning through a set of annotated examples.

Analogy inference models on the other hand is supposed to determine if two pieces of text can be viewed as the same in higher level of abstraction. In a similar way to entailment, analogy recognition models assign a score to a pair of text fragments to evaluate their level of analogy. However, we note that this task is different from the traditional textual entailment task. For example, “earth orbits the sun” and “electron rotates around nucleus” can be viewed as analogous as both are stating the fact that ‘one object revolves around another’, but truth of one of them cannot be logically inferred from truth stated in the other. Accordingly, analogy between two pieces of text cannot be directly assessed through logical inference by standard models of textual entailment separate models is required to perform this task. To this end, we adopt multiple models of textual inference to take analogical inference into account.

While more than 500k manually-written English sentence pairs with their state of their inference relationship are available to be used for training models for logical inference [60], generating a similar amount of annotated texts for analogical inference would be very expensive. Therefore, once all models in our system were trained for logical inference over SNLI data-set [60], analogical inference is incorporated into graph matching and transformation-based textual inference models by introducing new set of rules. These models were then used to train the neural reasoning model. Design-related knowledge incorporated in the models from a set of engineering ontologies[9–11], function hierarchy[58], and machine reading of patent texts.

Our models depend on dependency graphs for representation of information in the text. While deep logical representations [61] may capture additional aspects of the semantics of the text, their much higher complexity makes them more vulnerable to inaccuracies and errors involved in such a semantic parsing process – the process of generating logical representations from text. Moreover, various structural information required for inference can be found in the syntactic representations such as dependency parse trees [62]. Syntactic parse trees were enriched by additional annotations by co-reference substitution and truth-value annotations according to [63].

Spatial model

Spatial models are likely the simplest models of analogy. In these models, concepts are represented as vectors in multi-dimensional spaces. Words can be denoted by vectors that reflect their linguistic information in such a way that words sharing common contexts in the corpus be located in close proximity to one another in this space. This context could be defined by documents in which words occurred, neighboring or grammatically dependent words. We initialized our word representations using the dependency-based word embedding [64] as it is shown to reflect less topical and more functional similarity than models such as skip-gram that consider neighboring words as the context. Our word embeddings were trained over 5 million of the latest patents of World Intellectual Property Organization (WIPO) published before Jan 2017. We applied retrofitting [65] on the word embeddings in order to leverage relational information from semantic lexicons and engineering ontologies to encourage words in the same category to have similar vector representations. Using Faruqui's retrofitting tool, we retrofitted the word embeddings on WordNet [66], FrameNet [67], and the Paraphrase Database [68] in addition to engineering ontologies and function hierarchy [58]. Words can have different senses in different context, in order to take this into account, retrofitted vectors were adjusted to the context according to methodology suggested in [69]. Our sentence vectors are obtained simply by taking mean values of these contextualized word-vectors, although more sophisticated models such as Skip-Thought[70] or Paragraph-vector which take distributional semantics of sentences into account might reflect the compositional semantics of sentences better, however, since we hybrid this model with more complex neural models this extra accuracy might not be as significant.

Graph matching model

Spatial models of analogy won't capture all aspects of analogy[71], and more structured models are required to grasp relational aspects of concepts in more explicit way. In graph-matching models, the level of alignment between dependency-graphs of two texts are measured, score of each alignment edge is calculated based on its importance and the overall matching score is computed by summing up all alignments scores involved. This model includes an optimization algorithm which finds the matching with maximum total alignment score.

To incorporate analogical inference into this model, we added up new rules for lexical substitution based on path similarities in ontologies and word embedding [72] to existing rules proposed in [73] for logical inference. This allows for entities from same ontologies to be matched in two sentences with high alignment score. A schematic illustration of the text-based analogy-making based graph matching model is depicted in Figure 1. *Valve-transistor*, *resistance-width* pairs are semantically distant from each other and consequently receive high matching cost. In contrary, *control -regulate*, *flow-current*, *through -by*, *changing -adjusting* as well as dependency relationships are semantically close and accordingly receive a low matching cost, the overall cost of matching between two sentences turns out to be low.

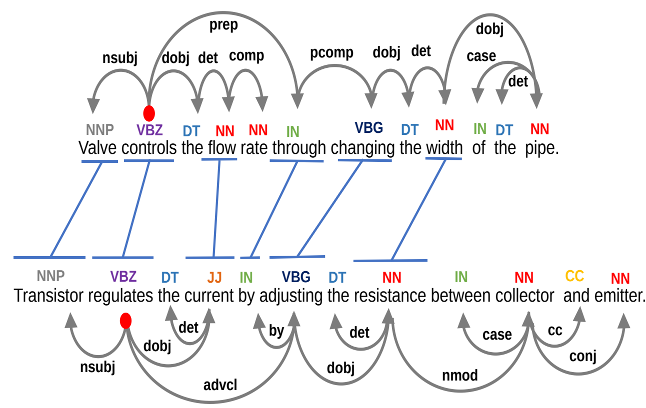

Figure 1. Graphical illustration of graph matching model of analogy. Red dots denote roots of dependency trees. (See [3] for definitions of dependency labels)

Transformation-based Model

In the transformation based model, one piece of text is converted to another piece of text through a set of partial transformations. Each partial-transformation is assigned a score proportional to amount of similarity between meaning of transformed sentence and current sentence, and overall score is computed by adding up scores of all partial-transformations. The model includes a search algorithm which looks for the sequence of partial-transformations that leads to maximum total score. Similar to graph-matching model we added up a transformation rules based on lexical substitution according to a set of ontologies and a word embedding lexical substitutability

#	Valve controls the flow rate through changing the width of the pipe.
1	Valve regulates the flow rate by changing the width of the pipe.
2	Valve regulates the flow rate by changing the width of the pipe.
3	Valve regulates the flow rate by adjusting the width of the pipe.
4	Valve regulates the current by adjusting the width of the pipe.
5	Transistor regulates the current by adjusting the width of the pipe.
6	Transistor regulates the current by adjusting the resistance between collector and emitter.

Table 1. Sequence of transformation steps for analogy between two instance sentences for transformation-based model of analogy

onto the set of existing transformations, to allow for words of same ontology to be exchanged with each other.

Table 1 tabulates the sequence of transformations that converts one sentence into another. First, there are three transformations of relatively high score, namely substituting *by* with *through*, replacing *controls* with *regulates*, and exchanging *changing* with *adjusting*. The two final steps, (i.e. *transistor* with *valve* and the *width of the pipe* with *resistance between collector and emitter*) are comparatively of lower score. However, there is not a considerable change in the overall structure of the sentence, which makes the overall cost of transformations remains low. Detailed information on implementing such models are described in [73] and [63].

Neural Reasoning Model

Rule-based models are advantageous over neural models for textual inference, as we don't have access to a large amount of annotated data. Though these models perform fairly well for relatively short sentences where logical structure of texts are more obvious, they lack the generalization ability and therefore perform poorly on certain unseen text involving longer text fragments with complicated logical relations. Where a higher level of abstraction or collective inferences based on meaning of multiple sentences is essential. To make analogical models work in these more generic situations, we trained a neural reasoning system based on the results of two other models, so neural reasoning models learns how to generalize analogy into higher levels of abstraction.

Query as well as each sentence of the paragraph is represented by an array of word vectors where each word is represented with a multi-dimensional vector. Our neural reasoning system is a multi-layer deep neural architecture as depicted in Figure 2. This model is inspired by [74] for capturing logics embedded in higher levels of abstractions. It consists of one encoding layer and multiple reasoning layers. Our implementation has a few differences with Peng et al. [74]. In the encoder layer, we used tree- Long short-term memory (Tree-LSTM) instead of recursive neural networks. Tree-LSTMs allow for extracting long-dependencies in longer sentences. In addition to that, LSTMs perform "uniform credit assignment" and accordingly treating all inputs on the same level equally. It is important, as the first word may be as important for learning as the last word. Different from a linear-chain LSTM, a Tree-LSTM also allows for capturing the structure of the sentences and dependencies among words of the sentence. The encoder layer converts the question and sentences from natural language to vector representations through the child-sum tree-LSTMs. With the obtained representations from the encoding layer, the reasoning layer recursively updates through the interaction between question representation and fact representations. Intuitively, this interaction models the reasoning, including

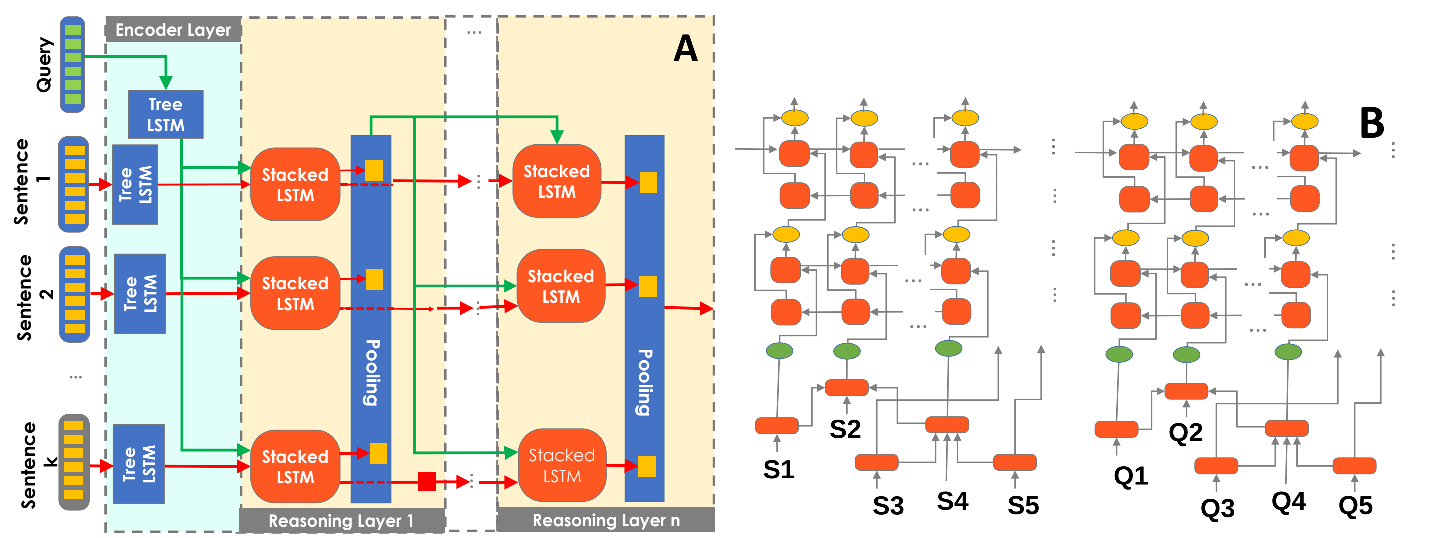

Figure 2.A illustrates architecture of our Neural Analogy Reasoner with n reasoning layers operating on one query and k sentences. Qi and Si represent respectively word vectors associated with i_{th} word of a sentence and a query, Figure 2.B displays the coupling between Tree-LSTM and Stacked-LSTM.

#	Multi-phase + additive + manufacturing + system	Multiphase + additive + manufacturing	Multiphase + “additive manufacturing”
1	“Additive manufacturing system and method with interchangeable cartridges for printing customized chocolate confections”	“Metal multiphase material and manufacturing method therefore”	“Metal multiphase material and manufacturing method therefore “
2	“Additive manufacturing system and method for printing customized chocolate confections”	“Multiphase separation system”	“Additive manufacturing system and method with interchangeable cartridges for printing customized chocolate confections “
3	“System and method for an integrated additive manufacturing cell for complex components”	“Multi-phase distribution system, sub-sea heat exchanger and a method of temperature control for hydrocarbons”	“System and method for an integrated additive manufacturing cell for complex components “
4	“Method and system for monitoring additive manufacturing processes”	“Multiphase lubricant concentrates for use in water based systems in the field of exploratory soil drilling”	“Multi-phase magnetic component and method of forming “
5	“Multi-scale mesh modelling software products and controllers “	“Density-based separation of biological analytes using multiphase systems”	“Feedstocks for additive manufacturing and methods for their preparation and use “
6	“Metal multiphase material and manufacturing method therefore”	“Multiphase systems having multiple phase properties”	“Bio-inspired method to obtain multifunctional dynamic nanocomposites “
7	“ Additive manufacturing of ceramic turbine components by transient liquid phase bonding using metal or ceramic binders”	“Density-based separation of biological analytes using multiphase systems”	“Methods of manufacturing divided blades of turbomachines by additive manufacturing”

Table 2. First seven patents ranked by Google/Patents for three sets of keywords associated with *‘Multi-phase additive manufacturing system’* key problem descriptor.

examination of the facts and comparison between the facts and the question. Different from [74], we used stacked bi-directional LSTMs for our reasoning layers, as it shown to produce more sound results for larger segments of texts, we also did not use have any soft-max layer at the end and final score of analogy is generated by the last reasoning layer. Step-by-step training procedure of whole models is described in Appendix 1.

Retrieval System

In analogy retrieval system, we need to go through all pieces of text in the patent repository and score their analogy with the query. For simplicity, we limit on the analysis at the paragraph level rather than at the entire document (entire text of patents) level. We split patent texts into their paragraphs and assess analogy of each paragraph with the query. Iterating through all pieces of text with the ensemble model is computationally expensive (our current repository includes 5 million patents published in WIPO published before Jan 2017). As accuracy of individual analogy models were found to be fairly low to generate meaningful results for the end-user, we modified and combined multiple models onto an ensemble model to achieve acceptable level of accuracy. Our ensemble model is a simple linear support vector regression which combines scores form different analogy models. However, running ensemble model with high accuracy which requires running all models together over entire text of all patents is extremely time consuming. So in order to enhance computational efficiency, the ranking is performed in multi-stage, in first stage only one model is used in ensemble model, only the fraction who ranked higher are ranked in next stage with an ensemble including two models, this is repeated for small and smaller fraction for 3 and 4 models involved. This ranking strategy shown to help improving computational efficiency without significantly harming accuracy of ranking.

CASE STUDY EVALUATION OF ANALOGY RETRIEVAL EFFICACY

The case study utilized here was to evaluate the methodology in the design of an additive manufacturing system intended to 3D print materials existing in at least two different phases, each material phase exhibiting radically different material properties. Criteria further include doing so in an inexpensive and reliable way. According to this description, key textual problem descriptors include:

“Multi-phase additive manufacturing system”
"3D print with materials in at least two different phases"
"Lower the cost of a large scale 3D printer"
"Achieve reliable interfaces between materials with radically different material properties"

To show how our analogical design concept retrieval system can assist designers when exploring patents, we compare our tool with google/patents as commonly used for searching patents. As observable form Table 2, even minor changes in the wording of the query may have considerably impact on the ranking of the patents.

#	Accumulative + Multiphase + Manufacturing	Additive + Multiphase + Lamination
1	"Multiphase meter to provide data for production management"	"Biodegradable multiphase compositions based on starch "
2	"Method and apparatus for separating and measuring solids from multi-phase well fluids"	"Modified multiphase bitumen composition and floor covering "
3	"Device and method for eliminating severe slugging in multiphase-stream flow lines"	"Tape casting slurry for laminated sheet type electronic component and preparation method for tape casting slurry "
4	"Multiphase clock generation and calibration"	"Multi-phase magnetic component and method of forming "
5	"Multiphase Separation System "	"Cloth-like synthetic textiles "
6	"Metal multiphase material and manufacturing method therefore"	"A process for preparing multiphase toilet soap "
7	"Method and apparatus for reading image data from an image sensor"	"Electric motor with laminated sheet windings"

Table 3. First seven patents ranked by Google/Patents for two sets of keywords associated with "Multi-phase additive manufacturing system" key problem descriptor after replacing terms with their sister-terms in WordNet.

In 4th, 5th, 7th, 8th and 10th ranked patent obtained for the first query, although "multi" and "phase" can be found in the document individually, "multi-phase" cannot be found as a unique unit, in 3rd and 9th patent, "multi-phase" is used for completely different semantic meaning which is not related to the materials utilized for manufacturing. Only in cases first and second patents "multi-phase" is used in its correct meaning which we consider as "near" analogy. In the next query, we use "multiphase" to avoid "multi" and "phase" to be taken apart in different word. We would have the similar issue but this time for

1	"3D printing device suitable for multi-material workpieces"
2	"Systems and methods for additive manufacturing of heterogeneous porous structures and structures made therefrom"
3	"Methods for fabricating gradient alloy articles with multi-functional properties"
4	"Method of forming a heterogeneous composite insulating layer of silicon dioxide in multilevel integrated circuits"
5	"Heat sealable biodegradable packaging material, its manufacturing method and a product package made therefrom"
6	"Method of forming hybrid metal ceramic components"
7	"Additive manufacture of turbine component with multiple materials"

Table 4. First seven patents ranked by our retrieval system for *Multi-phase additive manufacturing system* key problem descriptor.

'additive manufacturing', in all patents obtained from this query except the first one, "additive" is used to describe a chemical rather than manufacturing method. In the last query, we use "multiphase" and "additive manufacturing" again to avoid unwanted results, but again only three search results associated with this keywords are relevant, in the remaining either "additive manufacturing" is just used marginally (i.e. used in references or examples) or there is not any connection between additive manufacturing and multi-phase.

Table 3 lists results obtained from Google/Patents after replacing terms with their sister-terms in WordNet. *Additive manufacturing"* as a unit did not lead to any results in WordNet, *MultiPhase* also did not lead to any hypernym and only a synonym *PolyPhase* in WordNet. However *Additive* and *Manufacturing* separately lead to a few sister terms. We found *accumulative* and *Lamination* relevant as exchange terms. In none of these series of results were *manufacturing* or *Lamination* used in relation with *accumulative* or *Additive*.

The results of our system for "Multi-phase additive manufacturing system" problem descriptor is listed in Table 4. Since our system is based on sentence semantics, superficial form changes such as 'multi-phase' to 'multiphase' has no real effect on the results. We also get same first best results by substituting "additive manufacturing" with "3D printing".

In all of the closely related patents obtained, the patent describes a fabrication technique by which dissimilar materials are built into an object through incremental addition of materials. The first patent suggests making use of a rotary switchable nozzles which can be replaced for different materials. The second mainly targeted heterogeneous porous structures, it is based on forming a layer by applying a powder to a substrate and then a binder to the powder. A porogen applied to the powder in a determined pattern can then create extra layers. The seventh patent discussed new layer by layer manufacturing by combining selective laser sintering with selective laser melting of adjacent powder layers of different materials.

Based on comparison of google/patents retrieval system with results of our system for several queries, we found both that patents retrieved by google/patent are sensitive to keywords included in the query and that the relationships among keywords retrieved are not necessarily same as the query. In our system, the retrieved text segment contains semantically similar words with same relationships as the query. As such, our system may constitute a complementary or alternative option using the semantic analogy between the sentences rather than using analogous keywords.

CONCLUSIONS AND FUTURE-WORK

In comparing these analogical reasoning methods, the scope of vocabulary, complexity of task, computation time, accuracy (in terms of precision and recall) and implementation complexity are all trade-off factors. A patent data-base contains a broad technical vocabulary and so analogy-making is a comparatively complex task. Here, we have compensated implementation complexity and computation time in favor of accuracy. As such analysis of design requirements suits our application more than online web-search engines. We perform computations on local computing systems and speed it through parallel processing. We could further speed the computation through pre-processing static text.

With respect to future work, mental simulations and visual information have shown to play a significant rule in human design-analogy-making [7,75]. Since our methodology is purely text based, our algorithm falls short in accuracy when analogical inferences involves visual information in sketches or some sort of mental simulation is necessary. Consideration of image and dynamic based analogies remains to be studied for design concept analogical reasoning.

In this article, we introduced a new computational approach for retrieving useful analogies from the WIPO patent data-base based on analogy recognition accounting for the relation structure of the text. In order to build this model, we incorporated analogy into existing models of textual inference and combined them into an ensemble model to enhance accuracy of analogy recognition. Design-related knowledge used in the models includes engineering ontologies and the function hierarchy. We have demonstrated that this system is able to extract more relevant analogies from the patent repository for a case-study design problem as compared to *Google/Patents*.

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APPENDIX 1. TRAINING PROCEDURE

Models has to set their parameters by capturing information from the training data. Following protocol has been followed to learn parameters for all models.

1. All embedding were trained on latest 5 million patents of WIPO and retrofitted using Faruqi's retrofitting tool [65].
2. Tree-LSTM encoder layers were trained on 5 million latest patents of WIPO following the protocol suggested by Tai at al. [76].
3. Models were trained separately on 85% of Stanford Natural Language Inference (SNLI) data following the procedures provided in [75,69 ,79]. SNLI data trains the system for logical inference. Function hierarchy[64] as well as engineering ontologies[9–11] were used along with WordNet in graph matching and transformation based models. New rules as described in the paper were added to the set of rules in these models to enable analogy recognition.
4. A linear support vector regressor ensemble classifier is trained based on remaining 15% of SNLI data set
5. The ensemble model results were used to retrieve analogies for 2 million random paragraphs taken from patent repository.
6. Neural reasoning model is then trained on first 5 results of each retrieval based on scores obtained from ensemble of other three models.
7. An ensemble model for all four models including neural networks used in analogy retrieval system.

