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Patterns And Machine Learning For The Extraction Of Action Relations In Discharge

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Abstract: *This paper focuses on the mapping of natural language sentences in written stories to a structured knowledge representation. This process yields an exponential explosion of instance combinations since each sentence may contain a set of ambiguous terms, each one giving place to a set of instance candidates. The selection of the best combination of instances is a structured classification problem that yields a high demanding combinatorial optimization problem which, in this paper, is approached by a novel and efficient formulation of a genetic algorithm, which is able to exploit the conditional independence among variables, while improving the parallel scalability. The automatic rating of the resulting set of instance combinations, i.e. possible text interpretations, demands an exhaustive exploitation of the state-of-the-art resources in natural language processing to feed the system with pieces of evidence to be fused by the proposed framework. In this sense, a mapping framework able to reason with uncertainty, to integrate supervision, and evidence from external sources, was adopted. To improve the generalization capacity while learning from a limited amount of annotated data, a new constrained learning algorithm for Bayesian networks is introduced. This algorithm bounds the search space through a set of constraints which encode information on mutually exclusive values. The mapping of natural language utterances to a structured knowledge representation is important in the context of game construction, e.g. in an RPG setting, as it alleviates the manual knowledge acquisition bottleneck. The effectiveness of the proposed algorithm is evaluated on a set of three stories, yielding nine experiments. Our mapping framework yields performance gains in predicting the most likely structured representations of sentences when compared with a baseline algorithm.*
Keyword: *Natural language, State-of-the-art, Structured knowledge representations*

I. Introduction

The narrative provides a model for communicating experience and culture. Automatically extracting structured information from narrative text is a challenging task, since the structured representation of connected events and behaviors may involve commonsense inferences based on background knowledge, such as the semantic representation of objects, their properties and behavior, the motivations and goals behind the actions of characters, their emotional outcomes, and the actions they can undertake in the environment. The main research question of this paper is whether it is possible to provide a specific structured representation for narratives by fusing information from different sources and bounding the domain to a finite set of actions within the context of the current narrative. In this sense, this paper reports the results of our work on the knowledge representation for virtual worlds to answer the question “Who did What to Whom, and How, When and Where?”, similar to the current Semantic Role Labeling (SRL) algorithms [1]. However, the SRL aims at a general-purpose semantic representation, i.e. it aims at providing a semantic representation at a higher-level of abstraction, while our work aims at instantiating semantic frame elements at a lower-level of abstraction, in an annotation style tailored for the narrative text. Therefore, we model the problem as a structured prediction task within a framework able to incorporate other sources of information, besides the text and the language model, to deal with the challenging task of instantiating semantic frame elements at lower-level of abstraction. The statistical reasoning is carried out by a special formulation of a genetic algorithm, which exploits the conditional independence between variables. There have been efforts in information extraction from textual sources, where the goal is to identify specific semantic components, such as people, objects, and actions, whose types are known ahead of time. Typically in information extraction [2] semantic labels are defined beforehand, and data are collected to train machine learning classifiers. On the sentence level, there are several schemes for recognizing the basic semantic roles of the sentence constituents, i.e. the who, does what, where, when constituents, the most popular approaches being based on PropBank [3] and FrameNet [4] labels and their associated annotated corpora [5]. This entails work on finding the arguments of a semantic frame that is verb-centered, i.e. where the action or state is expressed by a verb in the sentence, and noun-centered. Some works, such as [6], aim at determining the character intentions, to provide the motivations for the actions performed. In the first instance this information can be useful in supporting the narrative interpretation, but in a second instance it can also improve the accuracy in predicting the correct action [7]. Our current framework does not model the character intentions; however, it makes possible to model these intentions, besides complex temporal, spatial or causal relationships in its Bayesian network based modeling. On the discourse level, two recent tasks are the identification of events and entities that have a temporal or spatial impact and the linking of such events and entities with temporal or spatial relations. Researchers have been interested in building such models for decades [8], but recent progress has been encouraged by the construction of corpora like the TimeBank, [9], and corpora with spatial information [10], which provide events and times beyond temporal and spatial relations, annotated on English data. Researchers have also investigated methods for modeling sequences of events using recurrent neural networks [11].

Another important task is assigning narrative roles to characters in stories, since it can help in improving the accuracy of the structured representation of the narrative, e.g. by modeling the relationship between the characters through graphical models encoding latent variables representing the character role in the narrative. In [12] the authors propose to combine NLP techniques with narrative domain knowledge in order to automatically identify characters and their roles in the story according to Propp's theory [13], in which the character role is categorized into broad categories, such as hero, villain, dispatcher, donor, magical helper, prize, and false hero. In this sense, it is also important to identify mental affect states. The work [14] introduced the plot units as a structured knowledge representation for narrative stories. Plot units focus on the affect states of characters and the tensions between them. To automatically produce plot unit representations for narrative text, some works use affect projection rules to map the affect states onto the characters in the story [15]. To do so, they create a lexicon consisting of patient polarity verbs (PPVs) that reflect world knowledge about desirable/undesirable states for animate beings. A large corpus of narratives deeply-annotated according to Vladimir Propp's theory was made available as a result of the work of Finlayson [16].The machine learning method adopted in this work, i.e. Bayesian network, has yielded reliable results in modeling narrative reasoning. For instance, in [17] the authors introduce a framework for machine-learning director agent strategies from observations of human-to-human interactions in an educational interactive narrative. The work The machine learning method adopted in this work, i.e. Bayesian network, has yielded reliable results in modeling narrative reasoning. For instance, in [17] the authors introduce a framework for machine-learning director agent strategies from observations of human-to-human interactions in an educational interactive narrative. The work utilized a Wizard-of-Oz paradigm where human wizards directed participants through Crystal Island's mystery storyline by dynamically controlling narrative events in the game. Interaction logs yielded training data to model the conditional probabilities of a dynamic Bayesian network model of the human wizards' directorial actions, achieving higher performance than naive Bayes and bi-gram model techniques. Text understanding also involves co reference resolution, i.e. to identify when two mentions of an entity refer to the same thing or person in the real world [18], for instance, recognizing the entity to which him and it refer in the discourse, which is context-dependent, so many different interpretations of a text are possible.

1.1 Cloud computing Cloud computing is a computing paradigm, where a large pool of systems are connectedin private or public networks, to provide dynamically scalable infrastructure for application, data and file storage. With the advent of this technology, the cost of computation, application hosting, content storage and delivery is reduced significantly. Cloud computing is a practical approach to experience direct cost benefits and it has the potential to transform a data center from a capital-intensive set up to a variable priced environment. The idea of cloud computing is based on a very fundamental principal of „reusability of IT capabilities'. The difference that cloud computing brings compare to traditional concepts of "grid computing", "distributed computing", "utility computing", or "autonomic computing is to broaden horizons across organizational boundaries. Forrester defines cloud computing as:"A pool of abstracted, highly scalable, and managed compute infrastructure capable of hosting end-customer applications and billed by consumption.

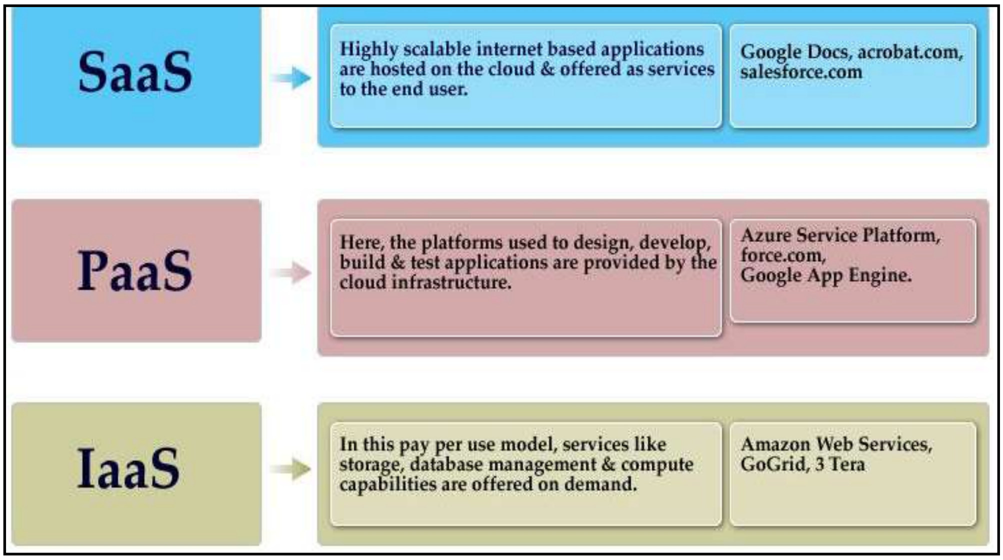
1.2 Cloud Computing Models

Cloud Providers offer services that can be grouped into three categories.

Software as a Service (SaaS): In this model, a complete application is offered to the customer, as a service on demand. A single instance of the service runs on the cloud & multiple end users are serviced. On the customers‟ side, there is no need for upfront investment in servers or software licenses, while for the provider, the costs are lowered, since only a single application needs to be hosted & maintained. Today SaaS is offered by companies such as Google, Salesforce, Microsoft, Zoho, etc.

Platform as a Service (Paas): Here, a layer of software, or development environment is encapsulated & offered as a service, upon which other higher levels of service can be built. The customer has the freedom to build his own applications, which run on the provider‟s infrastructure. To meet manageability and scalability requirements of the applications, PaaS providers offer a predefined combination of OS and application servers, such as LAMP platform (Linux, Apache, MySql and PHP), restricted J2EE, Ruby etc. Google‟s App Engine, Force.com, etc are some of the popular PaaS examples.

Infrastructure as a Service (Iaas): IaaS provides basic storage and computing capabilities as standardized services over the network. Servers, storage systems, networking equipment, data centre space etc. are pooled and made available to handle workloads. The customer would typically deploy his own software on the infrastructure. Some common examples are Amazon, GoGrid,3Tera, etc.



Understanding Public and Private Clouds

Enterprises can choose to deploy applications on Public, Private or Hybrid clouds. Cloud Integrators can play a vital part in determining the right cloud path for each organization.

Public Cloud

Public clouds are owned and operated by third parties; they deliver superior economies of scale to customers, as the infrastructure costs are spread among a mix of users, giving each individual client an attractive low-cost, "Pay-as-you-go" model. All customers share the same infrastructure pool with limited configuration, security protections, and availability variances. These are managed and supported by the cloud provider. One of the advantages of a Public cloud is that they may be larger than an enterprises cloud, thus providing the ability to scale seamlessly, on demand.

Private Cloud

Private clouds are built exclusively for a single enterprise. They aim to address concerns on data security and offer greater control, which is typically lacking in a public cloud. There are two variations to a private cloud:

- On-premise Private Cloud: On-premise private clouds, also known as internal clouds are hosted within one‟s own data center. This model provides a more standardized process and protection, but is limited in aspects of size and scalability. IT departments would also need to incur the capital and operational costs for the physical resources. This is best suited for applications which require complete control and configurability of the infrastructure and security.

Externally hosted Private Cloud: This type of private cloud is hosted externally with a cloud provider, where the provider facilitates an exclusive cloud environment with full guarantee of privacy. This is best suited for enterprises that don‟t prefer a public cloud due to sharing of physical resources.

Hybrid Cloud

Hybrid Clouds combine both public and private cloud models. With a Hybrid Cloud, service providers can utilize 3rd party Cloud Providers in a full or partial manner thus increasing the flexibility of computing. The Hybrid cloud environment is capable of public cloud can be used to manage any unexpected surges in workload.

II. Related Work

Tomas Mikolov, Kai Chen[1]We propose two novel model architectures for computing continuous vector representations of words from very large data sets. The quality of these representations is measured in a word similarity task, and the results are compared to the previously best performing techniques based on different types of neural networks. We observe large improvements in accuracy at much lower computational cost, i.e. it takes less than a day to learn high quality word vectors from a 1.6 billion words data set. Furthermore, we show that these vectors provide state-of-the-art performance on our test set for measuring syntactic and semantic word similarities.

Oswaldo Ludwig, Xiao Liu, Parisa Kordjamshidi, Marie-Francine Moens[2]This paper introduces the visually informed embedding of word (VIEW), a continuous vector representation for a word extracted from a deep neural model trained using the Microsoft COCO data set to forecast the spatial arrangements between visual objects, given a textual description. The model is composed of a deep multilayer perceptron (MLP) stacked on the top of a Long Short Term Memory (LSTM) network, the latter being preceded by an embedding layer. The VIEW is applied to transferring multimodal background knowledge to Spatial Role Labeling (SpRL) algorithms, which recognize spatial relations between objects mentioned in the text. This work also contributes with a new method to select complementary features and a _ne-tuning method for MLP that improves the F1 measure in classifying the words into spatial roles. The VIEW is evaluated with the Task 3 of SemEval-2013 benchmark data set, Space Eval.

Elahe Rahimtoroghi, Thomas Corcoran, Reid Swanson, and Marilyn A. Walker[3]The increased use of large corpora in narrative research has created new opportunities for empirical research and intelligent narrative technologies. To best exploit the value of these corpora, several research groups are eschewing complex discourse analysis techniques in favor of high-level minimalist narrative annotation schemes that can be quickly applied, achieve high inter-rater agreement, and are amenable to automation using machine-learning techniques. In this paper we compare different annotation schemes that have been employed by two groups of researchers to annotate large corpora of narrative text. Using a dual annotation methodology, we investigate the correlation between narrative clauses distinguished by their structural role (orientation, action, evaluation), their subjectivity, and their narrative level within the discourse. We find that each simple narrative annotation scheme captures a structurally distinct characteristic of real-world narratives, and each combination of labels is evident in a corpus of 19 weblog narratives (951 narrative clauses). We discuss several potential applications of minimalist narrative annotation schemes, noting the combination of label across these two annotation schemes that best support each task.

Eric Bigelow, Daniel Scarafoni, Lenhart Schubert,and Alex Wilson[4]There is ample evidence that human understanding of ordinary language relies in part on a rich capacity for imagistic mental modeling. We argue that genuine language understanding in machines will similarly require an imagistic modeling capacity enabling fast construction of instances of prototypical physical situations and events, whose participants are drawn from a wide variety of entity types, including animate agents. By allowing fast evaluation of predicates such as `can-see', `under', and `inside', these model instances support coherent text interpretation. Imagistic modeling is thus a crucial {and not very broadly appreciated { aspect of the long-standing knowledge acquisition bottleneck in AI. We will illustrate how the need for imagistic modeling arises even in the simplest rst-reader stories for children, and provide an initial feasibility study to indicate what the architecture of a system combining symbolic with imagistic understanding might look like.

III. Proposed System

The system receives as input the narrative text in addition to the narrative domain, i.e. the sets of allowable slot values for the variables representing the action and its arguments, i.e. characters/avatars, items/objects, tools and movement directions, in accordance with the elements defined in the graphical framework. The proposed framework starts by extracting a set of cues from the text by using state-of-the-art algorithms for natural language processing.

IV. Modules

A. State-of-the-art

There have been efforts in information extraction from textual sources, where the goal is to identify specific semantic components, this module has the set of process like synthetic process, SRL and conference resolution this generate multiple content

B. Mapping to KR

KR module, which also receives the allowable variable values, i.e. the domain. The Mapping to KR module extracts vector representations from the set cues, i.e. the labeled tokens, by using a recurrent neural network based language model

C. Joint probabilistic

A joint probabilistic model over the set of variables is defined, learned, and inferred/instantiated by using a probabilistic inference algorithm .In our case a combinatorial optimization based on GA, in order to classify the most likely joint assignment to all of the labels simultaneously.

D. Baking

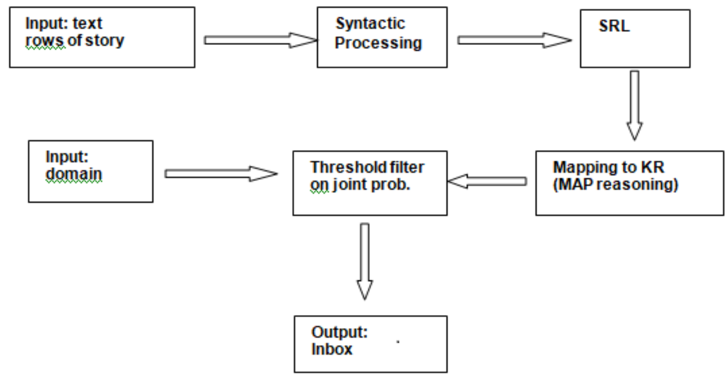
Create the separate login for banking department, each department has separate logging , when ever customer send's message to bank, process will find which department , message directly goes to respective departments

Algorithm 1 Combinatorial optimization by GA

1: **Input**: p, S, D, W, f, , , Npop: the selective pressure, p, the sentence, S, the dictionary, D, and its respective word representations,W, SRL and syntactic features, f, the sets of discrete variable values, and the number of GA individuals, Npop, respectively.
2: **Output**: X_, __: a vector with the indices of the optimal states of the variables and the optimal value of the fitness function (for frame filtering by thresholding) respectively.
3: Generate a set with Npop chromosomes fCrg of dimension _M for the initial population, in which each gene encodes the index of a state candidate of one of the variables belonging to the set , randomly generated in a uniform distribution, where the feasible values of the ith gene are natural numbers bounded into the interval [1; jSij];
4: **for** generation = 1 : maxgener **do**
5: **// Evaluating the population: //**
6: **for** ind = 1 : Npop **do**
7: [_x1; : : : ; _x _M] Crind: load the variables _X q, q =1; : : : ; _M, with the indices stored in the chromosome of the current individual;
8: **for** j = 1 : fM **do**
9: Exhaustive search for ex_jaccording to (19);
10: **end for**
11: Substitute ex_1; : : : ; ex_fM and _x1; : : : ; _x _Minto (17) and (18) to have the current values of _1 and _2;
12: _ind _1 + _2: storing the fitness of individual ind;
13: **end for**
14: Rank the individuals according to their fitness _ind;
15: Store=update the genes of the best individual in Cr_ and the last values of ex_1; : : : ; ex_ fM into the output vector X_;
16: Store=update the best fitness value __;
17**: // Performing the crossover: //**
18: **for** k = 1 : Npop **do**
19: // Randomly selecting the indices of parents by using the asymmetric distribution proposed in [31]: //
20: #j random number 2 [0; 1] with uniform distribution, j = 1; 2;
21: parentj round _(Npop □ 1) ep#j□1 ep□1 + 1_, j = 1; 2;
22: **// Assembling the chromosome Crson k : //**
23: **for** m = 1 : _M **do**
24: Randomly select a parent (i.e. between parent1 and parent2) to give the mth gene for the kth individual of the new generation:
25: Crson (k;m) <-Cr(parent1or2;m);
26: **end for**
27: **end for**

28: **end for**

VI. Diagram



VII. Conclusion

We introduced a framework to map text from written stories to a specific low-level KR. This new framework is able to reason with uncertainty, to integrate training from annotated data and constraints encoding information on mutually exclusive values, beyond evidence from external sources.

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