A Knowledge-based System for the Dynamic Generation and Classification of Novel Contents in Multimedia Broadcasting

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A Knowledge-based System for the Dynamic Generation and Classification of Novel Contents in Multimedia Broadcasting

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Abstract. In this work we exploit a recently introduced nonmonotonic extension of Description Logics, able to deal with the problem of knowledge invention via commonsense concept combination, to dynamically generate novel editorial contents in the context of a real broadcasting company: RAI - Radiotelevisione Italiana, the Italian public broadcaster. In particular, we introduce the system implementing such logic, i.e. DENOTER: Dynamic gEnerator of NOvel contents in mulTimEdia bRoadcasting (available online at the URL: `http://di.unito.it/denoter`), that has been applied and tested in the online multimedia platform of RAI (i.e. RaiPlay) as a tool for both the generation/suggestion of novel genres of multimedia on-demand contents and the reclassification of the available items within such new genres. Our system works by extracting the typical properties characterizing the available genres (with a standard information extraction pipeline) and by building novel classes of genres as the result of a *creative* combination of such extracted representations. We have tested DENOTER (i) by reclassifying the available contents in RaiPlay with respect to the new generated genres (ii) with an evaluation, in the form of a controlled user study experiment, of the feasibility of using the obtained reclassifications as recommended contents (iii) with a qualitative evaluation done with a small group of experts of RAI. The obtained results are encouraging and pave the way to many possible further improvements and research directions.

1 INTRODUCTION

Knowledge invention via conceptual recombination is an important generative phenomenon highlighting some crucial aspects of the knowledge processing capabilities in human cognition. Such ability, in fact, concerns high-level capacities associated to creative thinking and problem solving. Still, it represents an open challenge in the field of artificial intelligence [3]. Dealing with this problem, indeed, requires, from an AI perspective, the harmonization of two conflicting requirements that are hardly accommodated in symbolic systems [7]: the need of a syntactic and semantic compositionality (typical of logical systems) and the one concerning the exhibition of typicality effects. According to a well-known argument [20], in fact, prototypes (i.e. commonsense conceptual representations based on typical properties) are not compositional. The argument runs as follows: consider a concept like *pet fish*. It results from the composition of the concept *pet* and of the concept *fish*. However, the prototype of *pet fish* cannot result from the composition of the prototypes of a pet and a fish: e.g. a typical pet is furry and warm, a typical fish is grayish, but a typical pet fish is neither furry and warm nor grayish (typically, it is red). The *pet fish* phenomenon is a paradigmatic example of the difficulty to address when building formalisms and systems trying to imitate this combinatorial human ability. In this paper, we exploit a framework able to account for this type of human-like concept combination and we show how it can be used as a tool for the generation and the suggestion of novel editorial content. In particular, we adopt the recently introduced nonmonotonic extension of Description Logics (from now on DL, see [2]) able to reason on typicality and called $\mathbf{T}^{\textsf{CL}}$ (typicality-based compositional logic) introduced in [15, 13].

In this logic, "typical" properties can be directly specified by means of a "typicality" operator $\mathbf{T}$ enriching the underlying DL, and a TBox can contain inclusions of the form $\mathbf{T}(C) \sqsubseteq D$ to represent that "typical Cs are also Ds". As a difference with standard DLs, in the logic $\mathbf{T}^{\textsf{CL}}$ one can consistently express exceptions and reason about defeasible inheritance as well. Typicality inclusions are also equipped by a real number $p \in (0.5, 1]$ representing the probability/degree of belief in such a typical property: this allows us to define a semantics inspired to the DISPONTE semantics [22] characterizing probabilistic extensions of DLs, which in turn is used in order to describe different *scenarios* where only some typicality properties are considered. Given a KB containing the description of two concepts C_H and C_M occurring in it, we then consider only *some* scenarios in order to define a revised knowledge base, enriched by typical properties of the combined concept $C \sqsubseteq C_H \sqcap C_M$ by also implementing some heuristics coming from the cognitive semantics.

In this work we exploit the logic $\mathbf{T}^{\textsf{CL}}$ in order to dynamically generate novel knowledge by means of a mechanism for commonsense combination[7]. This generative and creative capacity has been tested

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[7] Other works have already shown how such logic can be used to model complex cognitive phenomena [15], creative problem solving [16, 12] and to build intelligent applications in the field of computational creativity [14]. Alternative approaches to the problem of commonsense conceptual combi-

in the context of a real multimedia broadcaster (RAI - RadioTelevisione Italiana) as a tool for both the suggestion of novel genres of multimedia on-demand contents of the online platform RaiPlay (`https://www.raiplay.it`) and for the reclassification of the available items within such new genres. We introduce the system DENOTER (Dynamic gEnerator of NOvel contents in mulTimEdia bRoadcasting) which, first, automatically builds prototypes of existing *basic* genres in RaiPlay (comedy, thriller, kids, horror, and so on) by extracting information about *concepts* or *properties* occurring with the highest frequencies in the textual descriptions of the multimedia contents available in the online platform[8]. Such prototypes are formalized by means of a $\mathbf{T}^{\mathsf{CL}}$ knowledge base, whose TBox contains both *rigid* inclusions of the form

$$BasicGenre \sqsubseteq Concept,$$

in order to express essential desiderata but also constraints, for instance $Musical \sqsubseteq Song$ (musical contents must have songs) and $Kids \sqsubseteq \neg Blood$ (due to law restrictions, contents available for kids must *not* contain blood), as well as *prototypical* properties of the form

$$p \ :: \ \mathbf{T}(BasicGenre) \sqsubseteq TypicalConcept,$$

representing typical concepts of a given genre, where p is a real number in the range $(0.5, 1]$, expressing the frequency of such a concept in items belonging to that genre: for instance, $0.72 \ :: \ \mathbf{T}(Comedy) \sqsubseteq Heaven$ is used to express that the typical comedy contains/refers to the concept Heaven with a frequency/probability/degree of belief of the 72%, and such a degree is automatically extracted by DENOTER from the description of multimedia contents currently available on RaiPlay and marked as belonging to such a genre.

Given the knowledge base with the prototypical descriptions of basic genres, DENOTER exploits the reasoning capabilities of the logic $\mathbf{T}^{\mathsf{CL}}$ in order to generate new *derived* genres as the result of the creative combination of two (or even more) basic or derived ones. DENOTER also reclassifies multimedia contents of RaiPlay taking the new, derived genres into account. Intuitively, a multimedia item belongs to the new generated genre if its metadata (name, description, title) contain all the rigid properties as well as at least the 30% of the typical properties of such a derived genre. In this respect, DENOTER can be seen as a "white box" recommender system, able to suggest to its users multimedia contents/episodes belonging to new genres by providing an explanation of such a recommendation: indeed, a content is suggested if it is classified in the new genre, obtained by combining typical properties of basic genres preferred by the users themselves, and such a combination is driven by the theoretical foundations of the logic $\mathbf{T}^{\mathsf{CL}}$.

We have also tested DENOTER by performing three different kinds of evaluation that are reported and discussed in Section 5, namely an automatic evaluation, an evaluation of the satisfaction of users, and a qualitative evaluation by a small group of experts of RAI, showing promising results.

nation have been recently discussed in [6], [11], [4]. The main advantages of $\mathbf{T}^{\mathsf{CL}}$ with respect to such approaches are detailed in [15].

[8] In RaiPlay, each multimedia item (e.g. TV series episodes, movies, etc.) is currently explicitly marked as belonging to one or more basic genres by the company owning the rights about such product.

2 THE DESCRIPTION LOGIC $\mathbf{T}^{\mathsf{CL}}$ FOR CONCEPT COMBINATION

In this section we briefly recall the basic concepts underlying the logic $\mathbf{T}^{\mathsf{CL}}$ [13, 15], used in the system DENOTER as the basis for the generation of new genres as the combination of two existing ones. This logic combines three main ingredients. The first one relies on the DL of typicality $\mathcal{ALC} + \mathbf{T_R}$ introduced in [8], which allows to describe the *protoype* of a concept. In this logic, "typical" properties can be directly specified by means of a "typicality" operator $\mathbf{T}$ enriching the underlying DL, and a TBox can contain inclusions of the form $\mathbf{T}(C) \sqsubseteq D$ to represent that "typical Cs are also Ds". As a difference with standard DLs, in the logic $\mathcal{ALC} + \mathbf{T_R}$ one can consistently express exceptions and reason about defeasible inheritance as well. For instance, a knowledge base can consistently express that "normally, athletes are fit", whereas "sumo wrestlers usually are not fit" by $\mathbf{T}(Athlete) \sqsubseteq Fit$ and $\mathbf{T}(SumoWrestler) \sqsubseteq \neg Fit$, given that $SumoWrestler \sqsubseteq Athlete$. The semantics of the $\mathbf{T}$ operator is characterized by the properties of *rational logic* [10], recognized as the core properties of nonmonotonic reasoning. $\mathcal{ALC} + \mathbf{T_R}$ is characterized by a minimal model semantics corresponding to an extension to DLs of a notion of *rational closure* as defined in [10] for propositional logic: the idea is to adopt a preference relation among $\mathcal{ALC} + \mathbf{T_R}$ models, where intuitively a model is preferred to another one if it contains less exceptional elements, as well as a notion of *minimal entailment* restricted to models that are minimal with respect to such preference relation. As a consequence, $\mathbf{T}$ inherits well-established properties like *specificity* and *irrelevance*: in the example, the logic $\mathcal{ALC} + \mathbf{T_R}$ allows us to infer $\mathbf{T}(Athlete \sqcap Bald) \sqsubseteq Fit$ (being bald is irrelevant with respect to being fit) and, if one knows that Hiroyuki is a typical sumo wrestler, to infer that he is not fit, giving preference to the most specific information.

As a second ingredient, we consider a distributed semantics similar to the one of probabilistic DLs known as DISPONTE [23], allowing to label inclusions $\mathbf{T}(C) \sqsubseteq D$ with a real number between 0.5 and 1, representing its degree of belief/probability, assuming that each axiom is independent from each others. Degrees of belief in typicality inclusions allow to define a probability distribution over *scenarios*: roughly speaking, a scenario is obtained by choosing, for each typicality inclusion, whether it is considered as true or false. In a slight extension of the above example, we could have the need of representing that both the typicality inclusions about athletes and sumo wrestlers have a degree of belief of 80%, whereas we also believe that athletes are usually young with a higher degree of 95%, with the following KB:

(1) $SumoWrestler \sqsubseteq Athlete$
(2) $0.8 \ :: \ \mathbf{T}(Athlete) \sqsubseteq Fit$
(3) $0.8 \ :: \ \mathbf{T}(SumoWrestler) \sqsubseteq \neg Fit$
(4) $0.95 \ :: \ \mathbf{T}(Athlete) \sqsubseteq YoungPerson$

We consider eight different scenarios, representing all possible combinations of typicality inclusion: as an example, $\{((2), 1), ((3), 0), ((4), 1)\}$ represents the scenario in which (2) and (4) hold, whereas (3) does not. Obviously, (1) holds in every scenario, since it represents a rigid property, not admitting exceptions. We equip each scenario with a probability depending on those of the involved inclusions: the scenario of the example has probability 0.8×0.95 (since 2 and 4 are involved) $\times (1 - 0.8)$ (since 3 is not involved) $= 0.152 = 15.2\%$. Such probabilities are then taken into account in order to choose the most adequate scenario describing the prototype of the combined concept.

As a third element of the proposed formalization we employ a method inspired by cognitive semantics [9] for the identification of a dominance effect between the concepts to be combined: for every combination, we distinguish a HEAD, representing the stronger element of the combination, and a MODIFIER. The basic idea is: given a KB and two concepts C_H (HEAD) and C_M (MODIFIER) occurring in it, we consider only *some* scenarios in order to define a revised knowledge base, enriched by typical properties of the combined concept $C \sqsubseteq C_H \sqcap C_M$.

Let us now present the logic $\mathbf{T}^{\mathsf{CL}}$ more in detail. The language of $\mathbf{T}^{\mathsf{CL}}$ extends the basic DL $\mathcal{ALC}$ by *typicality inclusions* of the form $\mathbf{T}(C) \sqsubseteq D$ equipped by a real number $p \in (0.5, 1]$ – observe that the extreme 0.5 is not included – representing its degree of belief, whose meaning is that "we believe with degree/probability p that, normally, Cs are also Ds" [9]

Definition 1 (Language of $\mathbf{T}^{\mathsf{CL}}$) *We consider an alphabet of concept names* $\mathtt{C}$*, of role names* $\mathtt{R}$*, and of individual constants* $\mathtt{O}$*. Given* $A \in \mathtt{C}$ *and* $R \in \mathtt{R}$*, we define:*

$$C, D := A \mid \top \mid \bot \mid \neg C \mid C \sqcap C \mid C \sqcup C \mid \forall R.C \mid \exists R.C$$

We define a knowledge base $\mathcal{K} = \langle \mathcal{R}, \mathcal{T}, \mathcal{A} \rangle$ *where:*
- $\mathcal{R}$ *is a finite set of rigid properties of the form* $C \sqsubseteq D$*;*
- $\mathcal{T}$ *is a finite set of typicality properties of the form*

$$p \ :: \ \mathbf{T}(C) \sqsubseteq D$$

where $p \in (0.5, 1] \subseteq \mathbb{R}$ *is the degree of belief of the typicality inclusion;*
- $\mathcal{A}$ *is the ABox, i.e. a finite set of formulas of the form either* $C(a)$ *or* $R(a, b)$*, where* $a, b \in \mathtt{O}$ *and* $R \in \mathtt{R}$*.*

A model $\mathcal{M}$ in the logic $\mathbf{T}^{\mathsf{CL}}$ extends standard $\mathcal{ALC}$ models by a preference relation among domain elements as in the logic of typicality [8]. In this respect, $x < y$ means that x is "more normal" than y, and that the typical members of a concept C are the minimal elements of C with respect to this relation[10]. An element $x \in \Delta^{\mathcal{I}}$ is a *typical instance* of some concept C if $x \in C^{\mathcal{I}}$ and there is no C-element in $\Delta^{\mathcal{I}}$ *more normal* than x. Formally:

Definition 2 (Model of $\mathbf{T}^{\mathsf{CL}}$) *A model* $\mathcal{M}$ *is any structure*

$$\langle \Delta^{\mathcal{I}}, <, .^{\mathcal{I}} \rangle$$

where:

- $\Delta^{\mathcal{I}}$ *is a non empty set of items called the domain;*
- $<$ *is an irreflexive, transitive, well-founded and modular (for all* x, y, z *in* $\Delta^{\mathcal{I}}$*, if* $x < y$ *then either* $x < z$ *or* $z < y$*) relation over* $\Delta^{\mathcal{I}}$*;*
- $.^{\mathcal{I}}$ *is the extension function that maps each atomic concept* C *to* $C^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}}$*, and each role* R *to* $R^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}} \times \Delta^{\mathcal{I}}$*, and is extended to complex concepts as follows:*
  - $(\neg C)^{\mathcal{I}} = \Delta^{\mathcal{I}} \setminus C^{\mathcal{I}}$
  - $(C \sqcap D)^{\mathcal{I}} = C^{\mathcal{I}} \cap D^{\mathcal{I}}$
  - $(C \sqcup D)^{\mathcal{I}} = C^{\mathcal{I}} \cup D^{\mathcal{I}}$
  - $(\exists R.C)^{\mathcal{I}} = \{x \in \Delta^{\mathcal{I}} \mid \exists (x, y) \in R^{\mathcal{I}}$ *such that* $y \in C^{\mathcal{I}}\}$
  - $(\forall R.C)^{\mathcal{I}} = \{x \in \Delta^{\mathcal{I}} \mid \forall (x, y) \in R^{\mathcal{I}}$ *we have* $y \in C^{\mathcal{I}}\}$
  - $(\mathbf{T}(C))^{\mathcal{I}} = Min_<(C^{\mathcal{I}})$*, where* $Min_<(C^{\mathcal{I}}) = \{x \in C^{\mathcal{I}} \mid \nexists y \in C^{\mathcal{I}}$ *s.t.* $y < x\}$.

A model $\mathcal{M}$ can be equivalently defined by postulating the existence of a function $k_{\mathcal{M}} : \Delta^{\mathcal{I}} \longmapsto \mathbb{N}$, where $k_{\mathcal{M}}$ assigns a finite rank to each domain element [8]: the rank of x is the length of the longest chain $x_0 < \ldots < x$ from x to a minimal x_0, i.e. such that there is no x' such that $x' < x_0$. The rank function $k_{\mathcal{M}}$ and $<$ can be defined from each other by letting $x < y$ if and only if $k_{\mathcal{M}}(x) < k_{\mathcal{M}}(y)$.

Definition 3 (Model satisfying a knowledge base in $\mathbf{T}^{\mathsf{CL}}$) *Let* $\mathcal{K} = \langle \mathcal{R}, \mathcal{T}, \mathcal{A} \rangle$ *be a KB. Given a model* $\mathcal{M} = \langle \Delta^{\mathcal{I}}, <, .^{\mathcal{I}} \rangle$*, we assume that* $.^{\mathcal{I}}$ *is extended to assign a domain element* $a^{\mathcal{I}}$ *of* $\Delta^{\mathcal{I}}$ *to each individual constant* a *of* $\mathtt{O}$*. We say that:*

- $\mathcal{M}$ *satisfies* $\mathcal{R}$ *if, for all* $C \sqsubseteq D \in \mathcal{R}$*, we have* $C^{\mathcal{I}} \subseteq D^{\mathcal{I}}$*;*
- $\mathcal{M}$ *satisfies* $\mathcal{T}$ *if, for all* $q \ :: \ \mathbf{T}(C) \sqsubseteq D \in \mathcal{T}$*, we have that* [11] $\mathbf{T}(C)^{\mathcal{I}} \subseteq D^{\mathcal{I}}$*, i.e.* $Min_<(C^{\mathcal{I}}) \subseteq D^{\mathcal{I}}$*;*
- $\mathcal{M}$ *satisfies* $\mathcal{A}$ *if, for each assertion* $F \in \mathcal{A}$*, if* $F = C(a)$ *then* $a^{\mathcal{I}} \in C^{\mathcal{I}}$*, otherwise if* $F = R(a, b)$ *then* $(a^{\mathcal{I}}, b^{\mathcal{I}}) \in R^{\mathcal{I}}$*.*

Even if the typicality operator $\mathbf{T}$ itself is nonmonotonic (i.e. $\mathbf{T}(C) \sqsubseteq E$ does not imply $\mathbf{T}(C \sqcap D) \sqsubseteq E$), what is inferred from a KB can still be inferred from any KB' with KB $\subseteq$ KB', i.e. the resulting logic is monotonic. As already mentioned, in order to perform useful nonmonotonic inferences, in [8] the authors have strengthened the above semantics by restricting entailment to a class of minimal models. Intuitively, the idea is to restrict entailment to models that *minimize the atypical instances of a concept*. The resulting logic corresponds to a notion of *rational closure* on top of $\mathcal{ALC} + \mathbf{T_R}$. Such a notion is a natural extension of the rational closure construction provided in [10] for the propositional logic. This nonmonotonic semantics relies on minimal rational models that minimize the *rank of domain elements*. Informally, given two models of KB, one in which a given domain element x has rank 2 (because for instance $z < y < x$), and another in which it has rank 1 (because only $y < x$), we prefer the latter, as in this model the element x is assumed to be "more typical" than in the former. Query entailment is then restricted to minimal *canonical models*. The intuition is that a canonical model contains all the individuals that enjoy properties that are consistent with KB. This is needed when reasoning about the rank of the concepts: it is important to have them all represented.

Given a KB $\mathcal{K} = \langle \mathcal{R}, \mathcal{T}, \mathcal{A} \rangle$ and given two concepts C_H and C_M occurring in $\mathcal{K}$, the logic $\mathbf{T}^{\mathsf{CL}}$ allows defining a prototype of the combined concept C as the combination of the HEAD C_H and the MODIFIER C_M, where the typical properties of the form $\mathbf{T}(C) \sqsubseteq D$ (or, equivalently, $\mathbf{T}(C_H \sqcap C_M) \sqsubseteq D$) to ascribe to the concept C are obtained by considering blocks of scenarios with the same probability, in decreasing order starting from the highest one. We first discard all the inconsistent scenarios, then:

[9] The reason why we only allow typicality inclusions equipped with probabilities $p > 0.5$ is due to our effort of integrating two different semantics: typicality based logic and DISPONTE. In particular, as detailed in [15] this choice seems to be the only one compliant with both the formalisms. On the contrary, it would be misleading to also allow low degrees of belief for typicality inclusions, since typical knowledge is known to come with a low degree of uncertainty.

[10] It could be possible to consider an alternative semantics whose models are equipped with multiple preference relations. However the approach based on a single preference relation in [8] ensures good computational properties (reasoning in the resulting nonmonotonic logic $\mathcal{ALC} + \mathbf{T_R}$ has the same complexity of the standard $\mathcal{ALC}$), whereas adopting multiple preference relations could lead to higher complexities.

[11] It is worth noticing that here the degree q does not play any role. Indeed, a typicality inclusion $\mathbf{T}(C) \sqsubseteq D$ holds in a model only if it satisfies the semantic condition of the underlying DL of typicality, i.e. minimal (typical) elements of C are elements of D. The degree of belief q will have a crucial role in the application of the distributed semantics, allowing the definition of scenarios as well as the computation of their probabilities.

- we discard those scenarios considered as *trivial*, consistently inheriting all the properties from the HEAD from the starting concepts to be combined. This choice is motivated by the challenges provided by task of commonsense conceptual combination itself: in order to generate plausible and creative compounds it is necessary to maintain a level of surprise in the combination. Thus both scenarios inheriting all the properties of the two concepts and all the properties of the HEAD are discarded since they prevent this surprise;
- among the remaining ones, we discard those inheriting properties from the MODIFIER in conflict with properties that could be consistently inherited from the HEAD;
- if the set of scenarios of the current block is empty, i.e. all the scenarios have been discarded either because trivial or because preferring the MODIFIER, we repeat the procedure by considering the block of scenarios, having the immediately lower probability.

Remaining scenarios are those selected by the logic $\mathbf{T}^{\mathsf{CL}}$. The ultimate output of our mechanism is a knowledge base in the logic $\mathbf{T}^{\mathsf{CL}}$ whose set of typicality properties is enriched by those of the compound concept C. Given a scenario w satisfying the above properties, we define the properties of C as the set of inclusions $p\ ::\ \mathbf{T}(C) \sqsubseteq D$, for all $\mathbf{T}(C) \sqsubseteq D$ that are entailed from w in the logic $\mathbf{T}^{\mathsf{CL}}$. The probability p is such that:

- if $\mathbf{T}(C_H) \sqsubseteq D$ is entailed from w, that is to say D is a property inherited either from the HEAD (or from both the HEAD and the MODIFIER), then p corresponds to the degree of belief of such inclusion of the HEAD in the initial knowledge base, i.e. $p\ :\ \mathbf{T}(C_H) \sqsubseteq D \in \mathcal{T}$;
- otherwise, i.e. $\mathbf{T}(C_M) \sqsubseteq D$ is entailed from w, then p corresponds to the degree of belief of such inclusion of a MODIFIER in the initial knowledge base, i.e. $p\ :\ \mathbf{T}(C_M) \sqsubseteq D \in \mathcal{T}$.

The knowledge base obtained as the result of combining concepts C_H and C_M into the compound concept C is called C*-revised* knowledge base, and it is defined as follows:

$$\mathcal{K}_C = \langle \mathcal{R}, \mathcal{T} \cup \{p\ :\ \mathbf{T}(C) \sqsubseteq D\}, \mathcal{A}\rangle,$$

for all D such that either $\mathbf{T}(C_H) \sqsubseteq D$ is entailed in w or $\mathbf{T}(C_M) \sqsubseteq D$ is entailed in w, and p is defined as above.

As an example, consider the following version of the *Pet-Fish* problem. Let KB contains the following inclusions:

$$Fish \sqsubseteq LivesInWater \quad (1)$$
$$0.6\ ::\ \mathbf{T}(Fish) \sqsubseteq Greyish \quad (2)$$
$$0.8\ ::\ \mathbf{T}(Fish) \sqsubseteq Scaly \quad (3)$$
$$0.8\ ::\ \mathbf{T}(Fish) \sqsubseteq \neg Affectionate \quad (4)$$
$$0.9\ ::\ \mathbf{T}(Pet) \sqsubseteq \neg LivesInWater \quad (5)$$
$$0.9\ ::\ \mathbf{T}(Pet) \sqsubseteq LovedByKids \quad (6)$$
$$0.9\ ::\ \mathbf{T}(Pet) \sqsubseteq Affectionate \quad (7)$$

representing that a typical fish is greyish (2), scaly (3) and not affectionate (4), whereas a typical pet does not live in water (5), is loved by kids (6) and is affectionate (7). Concerning rigid properties, we have that all fishes live in water (1). The logic $\mathbf{T}^{\mathsf{CL}}$ combines the concepts Pet and $Fish$, by using the latter as the HEAD and the former as the MODIFIER. The prototypical Pet-Fish inherits from the prototypical fish the fact that it is scaly and not affectionate, the last one by giving preference to the HEAD since such a property conflicts with the opposite one in the modifier (a typical pet is affectionate). The scenarios in which all the three typical properties of a typical fish are inherited by the combined concept are considered as trivial and, therefore, discarded, as a consequence the property having the lowest degree ($Greyish$ with degree 0.6) is not inherited. The prototypical Pet-Fish inherits from the prototypical pet only property (6), since (5) conflicts with the rigid property (1), stating that all fishes (then, also pet fishes) live in water, whereas (7) is blocked, as already mentioned, by the HEAD/MODIFIER heuristics. Formally, the $Pet \sqcap Fish$-revised knowledge base contains, in addition to the above inclusions, the following ones:

$$0.8\ ::\ \mathbf{T}(Pet \sqcap Fish) \sqsubseteq Scaly \quad (3')$$
$$0.8\ ::\ \mathbf{T}(Pet \sqcap Fish) \sqsubseteq \neg Affectionate \quad (4')$$
$$0.9\ ::\ \mathbf{T}(Pet \sqcap Fish) \sqsubseteq LovedByKids \quad (6')$$

In [15] we have shown that reasoning in $\mathbf{T}^{\mathsf{CL}}$ remains in the same complexity class of standard $\mathcal{ALC}$ Description Logics.

Theorem 1 *Reasoning in* $\mathbf{T}^{CL}$ *is* EXPTIME*-complete.*

3 GENERATING NOVEL GENRES FOR THE PLATFORM RAIPLAY

In this section we describe DENOTER, the system exploiting the logic $\mathbf{T}^{\mathsf{CL}}$ in order to generate and suggest novel editorial genres for RaiPlay (`https://www.raiplay.it`), the online platform of on-demand contents of the Italian multimedia broadcaster RAI (RAdio televisione Italiana, `http://www.rai.it`). DENOTER is implemented in Python and it makes use of the library `owlready2` (`https://pythonhosted.org/Owlready2/`) for relying on the services of efficient DL reasoners (like HermiT). DENOTER first builds a prototypical description of basic genres available in RaiPlay, namely: action/adventure, kids, comedy, drama, science fiction, horror, musical, religious, sentimental, and thriller. A screenshot of the platform is reported in the figure 1.

To this aim, a web crawler extracts metadata from multimedia contents available on the platform. More in detail, for each item (program, episode, etc.) the crawler extracts (i) the genre to which it belongs and (ii) the set of "significant" words (i.e., excluding prepositions, proper names, articles, etc.) occurring in the description of each item, as well as their frequency. These information are used in order to provide a description of each basic genre in terms of its typical properties in the logic $\mathbf{T}^{\mathsf{CL}}$, where the frequency of a concept/word for a genre is obtained from the number of occurrences of such a concept/word in the items belonging to that genre. The five properties with the highest frequency over 0.5 are included in the prototypical description of each basic genre. Formally, we have:

Definition 4 *Given a multimedia item* m*, let* $\mathcal{S}_m$ *be the set of significant concepts extracted for* m *by the web crawler, and let* $Concept \in \mathcal{S}_m$*. Let* $n_{m,Concept}$ *be the number of occurrences of* $Concept$ *in the description of* m*. We define the frequency* $f_{m,Concept}$ *of concept* $Concept$ *for the item* m *as*

$$f_{m,Concept} = \frac{n_{m,Concept}}{\sum_{D \in \mathcal{S}_m} n_{m,D}}.$$

Definition 5 *Given a basic genre* $Genre$*, let* $\mathcal{MI}$ *be the set of multimedia items assigned to/labelled as belonging to* $Genre$*, and let* $\mathcal{S}_{Genre}$ *be the set of the concepts occurring in such items, i.e.* $\mathcal{S}_{Genre} = \bigcup_{m \in \mathcal{MI}} \mathcal{S}_m$*, where* $\mathcal{S}_m$ *is as in Definition 4.*

Given a concept $Concept \in \mathcal{S}_{Genre}$ *and an item* $m \in \mathcal{MI}$*, let* $n_{m,Concept}$ *be the number of occurrences of* $Concept$ *in the description of* m*. We define* $n_{Genre,Concept}$ *the number of occurrences of*

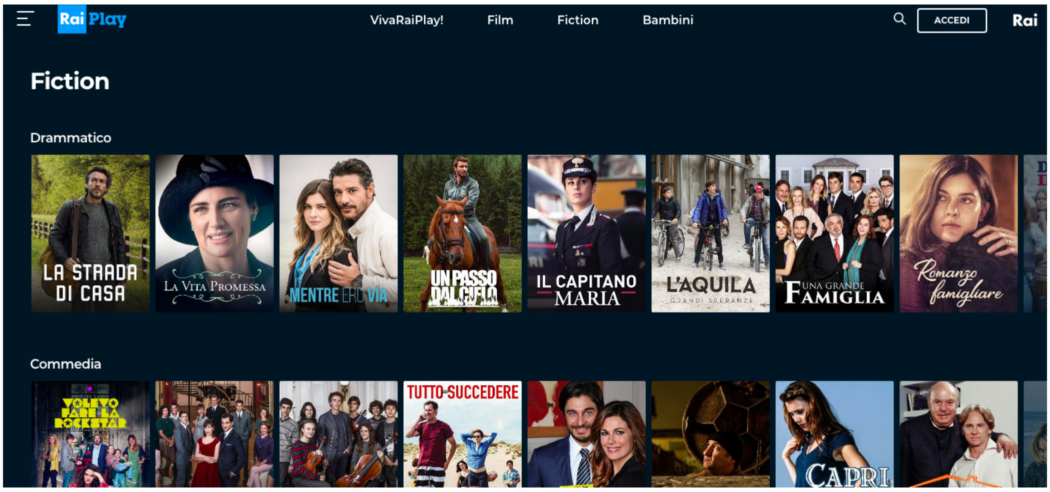

Figure 1. A screenshot of the RaiPlay platform.

Concept in the description of items of Genre, i.e.

$$n_{Genre,Concept} = \sum_{m \in \mathcal{MI}} n_{m,Concept}.$$

We also define the frequency of a concept Concept for a genre Genre, written $f_{Genre,Concept}$, as follows:

$$f_{Genre,Concept} = \frac{n_{Genre,Concept}}{\sum_{C \in \mathcal{S}_{Genre}} n_{Genre,C}}.$$

The prototypical description of a basic $Genre$ in the logic $\mathbf{T}^{\mathsf{CL}}$ is defined as the set of inclusions $p_1 :: \mathbf{T}(Genre) \sqsubseteq TypicalConcept_1$, $p_2 :: \mathbf{T}(Genre) \sqsubseteq TypicalConcept_2, \ldots$, $p_5 :: \mathbf{T}(Genre) \sqsubseteq TypicalConcept_5$, where $TypicalConcept_1$, $TypicalConcept_2, \ldots, TypicalConcept_5$ are the five concepts in $\mathcal{S}_{Genre}$ with the highest frequencies higher than 50%; frequencies are then also used as degrees of belief of the respective inclusions. Formally:

Definition 6 *Given a genre Genre, let the set of concepts $\mathcal{S}_{Genre}$ of Definition 5 in descending order by the frequencies $f_{Genre,Concept}$ of Definition 5:*

$$\mathcal{S}_{Genre} = \langle C_1, C_2, \ldots, C_k \rangle$$

where $f_{Genre,C_1} \geq f_{Genre,C_2} \geq \ldots \geq f_{Genre,C_k} > 0.5$. The prototypical description of Genre in the logic $\mathbf{T}^{\mathsf{CL}}$ is defined as the set of inclusions:

$$\begin{array}{l} f_{Genre,C_1} :: \mathbf{T}(Genre) \sqsubseteq C_1 \\ f_{Genre,C_2} :: \mathbf{T}(Genre) \sqsubseteq C_2 \\ \vdots \\ f_{Genre,C_5} :: \mathbf{T}(Genre) \sqsubseteq C_5 \end{array}$$

As an example, consider the basic genre $Religious$. The episodes/multimedia items labelled as belonging to such a genre are "Giacobbe", "Gesú di Nazareth" and "Francesco". All contain the word/concept God, whereas $Life$ appears in the two latter ones, and they are both in the five most frequent concepts.

In some cases, i.e. when possible, RAI experts have also manually added some rigid properties, thus integrating the bottom-up, data-driven, process of prototype formation with top down expert knowledge. In the example above, properties like $History$ and $Faith$, commonly associated to such genre, have been added. Therefore, the knowledge base generated by the crawler will contain, among others, the following inclusions :

$$\begin{array}{l} 0.9 :: \mathbf{T}(Religious) \sqsubseteq God \\ 0.7 :: \mathbf{T}(Religious) \sqsubseteq Life \\ Religious \sqsubseteq History \\ Religious \sqsubseteq Faith \end{array}$$

DENOTER generates novel hybrid genres by combining existing ones (by using the same logical procedure of the *pet-fish* problem). As an example, consider the following prototypes of basic genres $Kids$ and $Drama$:

$$\begin{array}{l} Kids \sqsubseteq \neg Sex \\ Kids \sqsubseteq \neg Homicide \\ 0.72 :: \mathbf{T}(Kids) \sqsubseteq Queen \\ 0.64 :: \mathbf{T}(Kids) \sqsubseteq World \\ 0.62 :: \mathbf{T}(Kids) \sqsubseteq Adventure \\ 0.6 :: \mathbf{T}(Kids) \sqsubseteq \neg DeadPerson \\ Drama \sqsubseteq \neg Happiness \\ 0.85 :: \mathbf{T}(Drama) \sqsubseteq Homicide \\ 0.83 :: \mathbf{T}(Drama) \sqsubseteq Life \\ 0.7 :: \mathbf{T}(Drama) \sqsubseteq DeadPerson \end{array}$$

DENOTER combines the two basic genres by implementing a variant of CoCoS [17], a Python implementation of reasoning services for the logic $\mathbf{T}^{\mathsf{CL}}$ in order to exploit efficient DLs reasoners for checking both the consistency of each generated scenario and the existence of conflicts among properties. More in detail, DENOTER considers both the available choices for the HEAD and the MODIFIER, and it allows to restrict its concern to a given and fixed number of inherited properties. As an example, the new, derived genre combining kids and drama with the limit fixed to four properties has the following $\mathbf{T}^{\mathsf{CL}}$ description (concept $Kids \sqcap Drama$):

$$\begin{array}{l} 0.83 :: \mathbf{T}(Kids \sqcap Drama) \sqsubseteq Life \\ 0.72 :: \mathbf{T}(Kids \sqcap Drama) \sqsubseteq Queen \\ 0.7 :: \mathbf{T}(Kids \sqcap Drama) \sqsubseteq DeadPerson \\ 0.64 :: \mathbf{T}(Kids \sqcap Drama) \sqsubseteq World \end{array}$$

Obviously, rigid properties of both basic concepts $Kids$ and $Drama$ are inherited by the derived concept, and this avoids the system to consider the property $Homicide$, even if it has the highest probability/degree of belief associated to the prototypical description of $Drama$. DENOTER is also able to involve *derived* genres in the concept combination, for instance we can combine derived genres $Action \sqcap Sentimental$ and the above $Kids \sqcap Drama$.

4 RE-CLASSIFICATION AND SUGGESTIONS OF MULTIMEDIA CONTENTS IN RAIPLAY

Apart from the process of automatic knowledge generation, DENOTER is also able to reclassify the multimedia items/episodes of RaiPlay within the novel derived genres (generated as described in the previous section). As mentioned, indeed, each multimedia item/episode is equipped by some information available in RaiPlay, namely: title, name of the program/episode, description of the program/serie, description of the episode. DENOTER extracts such information and then computes the frequencies of concepts in it as in Definition 4, in order to compare them with the properties of a derived genre. If the item contains all the rigid properties and at least the 30% of the typical properties of the genre under consideration, then the multimedia content is classified as belonging to it. Last, DENOTER suggests the set of classified contents, in a descending order of compatibility, where a rank of compatibility of a single item with respect to a genre is intuitively obtained as the sum of the frequencies of "compatible" concepts, i.e. concepts belonging to both the item and the prototypical description of the genre. Formally:

Definition 7 *Given a multimedia item m, let DerivedGenre be a derived genre as defined in Section 3 and let $\mathcal{S}_m$ be the set of concepts/words occurring in m as in Definition 4. Given a knowledge base KB of genres built by DENOTER, we say that m is compatible with DerivedGenre if the following conditions hold:*

1. *m contains all rigid properties of DerivedGenre, i.e.* $\{C \mid \mathit{DerivedGenre} \sqsubseteq C \in \mathit{KB}\} \subseteq \mathcal{S}_m$
2. *m contains at least the 30% of typical properties of DerivedGenre , i.e.*

$$\frac{\mid \mathcal{S}_m \cap \mathcal{S}_{\mathit{DerivedGenre}} \mid}{\mid \mathcal{S}_{\mathit{DerivedGenre}} \mid} \geq 0.3,$$

where $\mathcal{S}_{\mathit{DerivedGenre}}$ is the set of typical properties of DerivedGenre as in Definition 6.

As an example, consider the above derived genre $Kids \sqcap Drama$, and the multimedia items "Eneide" (`https://www.raiplay.it/programmi/eneide`) and "Raccontami" (`https://www.raiplay.it/programmi/raccontami`). They are both reclassified in the novel, generated genre $Kids \sqcap Drama$, since:

- all rigid properties of both basic genres are satisfied, that is to say neither Sex nor $Homicide$ nor $Happiness$ belong to the properties extracted by the crawler for both the items;
- more than the 30% of the typical properties of the derived genre are satisfied by the items, in particular "Eneide" has $Life$ with frequency 0.6, $Queen$ (0.65) and $DeadPerson$ (0.65), whereas "Raccontami" has $Life$ (0.62) and $Queen$ (0.6).

These two items will be then recommended by DENOTER in this order (thanks to its three compatible properties, "Eneide" will have a higher score with respect to "Raccontami").

It is worth noticing that DENOTER is applied to a single multimedia item, therefore it is normally applied to an episode of a given series, rather than to a whole series. This allows a finer selection of multimedia contents, since single episodes of a series often propose significantly different contents, then it could be plausible to suggest only some episodes to match the users' objectives.

5 EVALUATION AND DISCUSSION

DENOTER has been tested in a threefold way. The first evaluation is completely automatic and inheres the capability of the system of generating novel hybrid genres that are able to be populated by the original content of the RaiPlay platform via a re-classification mechanism involving the 4612 multimedia items of the platform. In this case, the success criterion concerns the avoidance of the creation of empty boxes corresponding to the new generated combined genres.

A second evaluation, aimed at measuring the satisfaction of the potential users of the platform when exposed to the contents of the novel categories suggested by DENOTER, consisted in a user study[12] involving 20 persons (5 females, 15 males, aged 20-35) that evaluated a total of 122 recommendations generated by the system. All the participants were selected from the same population, i.e., voluntary students at the Departments of Psychology and Computer Science of the University of Turin, using an availability sampling strategy. Participants were all naive to the experimental procedure and to the aims of the study. This evaluation was carried out as a classical "*one to one*" lab controlled experiment (i.e. one person at time with one expert interviewer) and we adopted a thinking aloud protocol[13]. At this stage, this solution was methodologically preferred with respect to the adoption of large scale online surveys since it allowed us to have more control on the type of thoughts and considerations emerging during the evaluation of the results. In this setting, the users had to start the interview by indicating a couple of preferred genres among those available in RaiPlay. This selection triggered both the activation of a novel hybrid prototypical genre by DENOTER and the corresponding reclassification of the RaiPlay multimedia contents based on such selection. The output of the system, pruned to show the top 5 best results, was then evaluated with a 1-10 voting scale expressing the satisfaction of the received recommendations.

The results and the insights of the first two evaluation are reported in Table 1. In particular, the first part of the table (*total*) reports respectively:

i the average reclassification results calculated for all the novel concepts generated by DENOTER (on average 180 items out of 4612 were reclassified for each novel genre obtained via concept combination);
ii the average user vote assigned by the users to the recommendations of the reclassified elements (with an average score of 6.5 out of 10). This score was calculated by considering, for each new category, the score assigned to the top 5 reclassified items, since they were provided, to the users, as recommendations for the novel genres.

The first column of the table also reports the details of the percentage of reclassified elements (calculated on the total of all the 4612 items

[12] This is one of the most commonly used methodology for the evaluation of recommender systems based on controlled small groups analysis, see [24].

[13] This technique consists in recording the verbal explanations provided by the people while executing a given laboratory task. It has been used in the AI literature since the pioneering work by Newell and Simon, as a source to individuate the heuristics used by humans to solve a given task [18, 19].

available in RaiPlay) for the combined genres obtained by considering the original selections by the users based on their preference. For the same set of novel combined genres, the second column reports the average score assigned by the users to the recommendations of each combined genre. Overall the obtained results are encouraging since the average rate assigned is above 6 (on a 1-10 scale).

Combined Genres	Automatic Reclassification 180 items per combination, 3.9% (total)	Average User Vote 6.5 out of 10 (total)
Thriller-Musical	1.3%	8.5
Thriller-Fantasy	1.3%	6.4
Thriller-Comedy	0.71%	4.7
Thriller-Action	2.9%	7.2
Romance-Thriller	1.7%	7
Romance-Comedy	1.4%	9
Romance-Drama	4.2%	5.4
Musical-Fantasy	2.4%	7.3
Musical-Comedy	1.89%	7.2
Musical-Action	4.29%	6.5
Fantasy-Thriller	1.25%	8
Fantasy-Comedy	0.84%	4.6
Fantasy-Action	2.5%	5.6
Drama-Thriller	3.2%	5
Drama-Fantasy	3.14%	6.5
Comedy-Romance	1.28%	7.5
Comedy-Musical	1.89%	4.6
Comedy-Drama	2.69%	7.6

Table 1. Combined results of the the first 2 evaluations.

A final, qualitative, evaluation was done with a small group of three experts of RAI in the form of an expert interview (the interview was carried out after a demo of the system and of its produced recommendations in RaiPlay). From this interview three main problematic elements emerged, that affected the overall quality (and therefore the assigned ratings) of the recommended items and that, once solved, can contribute to improve the accuracy of the recommendations. First, they pointed out how the quality of some recommendations (the low ranked ones) was affected by the fact that there was a misalignment between the textual *description* of the recommended item and the *content* of the recommended item: in fact, the descriptions associated to the items were not always reporting information about the content of the programme but sometimes only very generic information (e.g. describing the plot of a whole TV series and not of current episode) and this yielded - in some cases - to counter-intuitive results. Second: some of the (low ranked) items corresponded to very old TV episodes or movies done before the '60s. The recommendation of such items was somehow unexpected by the interviewed users, who expected to be exposed to more recent content (this particular problem emerged also during the thinking aloud protocol). Finally, the experts pointed out the importance of considering (in the initial selection phase) the possibility of expliciting also negative preferences (e.g. $\neg Kids$) in order to additionally filter out some unwanted content. Notably the first two of the above mentioned issues are not directly related to DENOTER, since: i) the system can not know if the association description/item is coherent, but it just provides (for the recommended output) the correspondence already in place in RaiPlay; ii) the recommendations of old editorial contents is based on the actual dataset of RaiPlay (collecting hundreds of TV shows, movies etc. from the 1954 to the recent days). This element can be overcome by simply adding an additional filter about the period preferences of the users. Finally, iii) the expression of negative preferences in DENOTER can be expressed by including the negation of the undesired prototypical descriptions. Overall all these issues can be addressed to improve the performance of the system and its adoption in the production phase. Overall the experts agreed in considering DENOTER as a good approach at addressing the very well known filter bubble effect [21], by introducing seeds of serendipity in content discovery by users. One fundamental discussion about the applicability of DENOTER in practice is whether or not it represents a truly innovative technical solution for a multimedia recommender system. The context in the latest years in this field is characterised by fervent research, which finds in the RecSys conference series the reference venue for publication[14]. According to [25] recommender systems "try to identify the need and preferences of users, filter the huge collection of data accordingly and present the best suited option before the users by using some well-defined mechanism". Despite the huge amount of proposals, the main families of recommender systems can be identified as based on: i) collaborative filtering; ii) content-based filtering; iii) hybrid filtering. At their core of functioning, collaborative filtering exploits similarities of usage patterns among mutually affine users, while content-based filtering exploits content similarity. DENOTER by definition falls into the latter category since in its current form it uses content description as the input. From the technical point of view, however, it differs from the current mainstream approaches that are mostly based on the comparison and matching of visual and aural features of the content [26, 5] by adding a logic framework capable of mapping and representing genuinely new intuitive principles influencing user preferences and usage attitudes which cannot be derived from the pure analysis of content and/or the comparison of similar users. Furthermore, it has a native adaptability to industrial contexts in which the editorial input has to be merged with automatic recommendation, since both kinds of input can be effectively processed by the same framework.

6 CONCLUSIONS AND FUTURE WORKS

In this work we have presented DENOTER, a knowledge-based system for the dynamic generation of novel media genres, exploiting the reasoning mechanism of the logic $\mathbf{T}^{\mathsf{CL}}$ in order to generate, reclassify and suggest novel content genres in the context of RaiPlay, the online platform of RAI. The system has been tested in threefold evaluation showing promising results for both the automatic evaluation and the user acceptability of the recommended items. In addition, a last evaluation conducted with experts has provided some valuable feedback that can be addressed in order to improve the results provided by the system (in particular for what concerns the recommendation phase).

The core component of the system DENOTER relies on CoCoS, a tool for combining concepts in the logic $\mathbf{T}^{\mathsf{CL}}$. In future research, we aim at studying the application of optimization techniques in [1] in order to improve the efficiency of CoCoS and, a consequence, of the proposed knowledge generation system. Secondly we aim at considering more accurate descriptions of media items than the online descriptions used in this work, namely Automatic Speech Recognition data and semantic visual categories extracted from video and audio channels of the content. Finally, as a mid-term goal, we plan to conduct a large scale experiment to further validate the effectiveness of the proposed approach.

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