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SIMULATION OF BACKGROUND KNOWLEDGE AND BRIDGING IN RUSSIAN

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This paper introduces a knowledge-based semantic approach towards bridging annotation of Russian texts. Our method simulates human background knowledge by using compact domain descriptions based on an extended version of SUMO ontology and lexical-semantic data from the “Universal Dictionary of Concepts”. Our approach supports a wide and extensible range of bridging relations. Out tool can build complex bridges with multiple arks based on assumptions and can be adapted to annotate other languages supported by the underlying dictionary of concepts.

Keywords: computational linguistics, bridging, reference, anaphora, linguistic ontology

МОДЕЛИРОВАНИЕ ФОНОВЫХ ЗНАНИЙ И ПОИСК АССОЦИАТИВНЫХ АНАФОР В ТЕКСТАХ НА РУССКОМ ЯЗЫКЕ

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1. Bridging

The notion of bridging, also known as indirect or associative anaphora, introduced by Clark [2] captures an essential mechanism of text interpretation inside a human mind. Every comprehensible piece of text contains some identifiable entities and statements about them. As we read or listen, we encounter new entities (new information) and refer them with previously mentioned ones (given information in Clark's terms). This is a way to construct a mental model of the reality described in the text. Pairs of related entities are viewed as a kind of anaphora where the previously given entity becomes the antecedent of the new. Unlike the common definition of anaphora, the relation between the entities in bridging is not limited to identity. It can be of any semantic type meaningful to the Listener. Building references requires deep background knowledge of the relevant domain, especially when the Speaker skips "redundant" details to improve the speed of communication. When the Listener fails to find a directly related antecedent of some new entity, he is forced to insert a suitable intermediate concept. This leads to creation of "bridges" with multiple "arks".

(1) На станции метро «Владыкино» в Москве найдено *взрывное устройство*.
Найденный предмет *обследовали* с использованием служебных **собак**.
(An *explosive device* was found at the Moscow underground station Vladykino.
The object was *examined* with service **dogs**)

Here the Listener assumes the existence of policemen, who were not mentioned directly, and constructs the following possible bridge: *explosive device* $^{\mathit{isObjectOf}}$ *examine* $^{\mathit{hasAgent}}$ *policemen* $^{\mathit{isUserOf}}$ *dog*. This assumption is based on common knowledge about police work and terrorism, implanted by television newscasts. It is possible to build arbitrarily long bridges by adding new assumptions.

Introduction of new concepts associated with the given information from background knowledge is also a productive mechanism of creativity. Its proper modeling combined with good plausibility filters might give an AI the ability to invent.

2. Overview of the approach

Existing works in the field of bridging fall into two groups: semantic approaches and syntactic ones. Syntactic approaches choose particular syntactic patterns, usually definite NPs, and treat the ability of certain words to fill such patterns as a criterion of a non-typed bridging relation. Later research by Hou [5] departs from a single pattern restriction, but still lacks the ability to explicitly represent the meaning of the detected bridging relations. The first published paper on bridging in Russian [9] follows the same path and uses Russian genitive NPs as the clue pattern.

A semantic approach always ascribes a semantic type to the discovered relations. The authors of such approaches often impose restrictions on the types of bridges they detect in order to accommodate to their resources and relation search methods. Papers by Poesio [7], Lassale [6] concentrate only on part-whole relations. Recasens [8], Zikánová [10], etc. add set-subset, cohyponymy, predicate-argument and symptom relations. Many studies rely on Princeton Wordnet as the source of lexical data and a knowledge base to estimate semantic relatedness of words. Unfortunately, English Wordnet provides only part of the information needed to simulate the mental mechanism of bridging. It offers good lexical coverage, usable (though poorly organized) taxonomy, but is very limited in the field of semantic relations other than part-whole. In particular, it lacks cause-result and predicate-role relations. Roitberg et al. [9]

wrote that absence of a (large scale) Russian Wordnet prevents the use of semantic methods on Russian material. We would answer that there are alternative resources for Russian and they have some advantages over the English Wordnet. One of them is briefly described in section 2.1.

We take a semantic approach based on a rich background knowledge base (KB). The target language is Russian, but our KB is a language-neutral semantic resource. As a result, our bridging tool can be adapted to work with other languages supported by the underlying semantic dictionary UNLDC [3] (English, Hindi, etc). Our project bears resemblance with the work by Fan [4], yet it is different in some key points. Both projects use a knowledge base encoded as a semantic graph and support simple taxonomy based inference. However, the structure and contents of the KBs are different. The set of relations in our study is wider. Our tool supports making assumptions and builds complex chain relations with intermediate concepts like the relation between the bomb and dogs in example 1.

2.1. Resources

Our relation search engine operates with ontology concepts instead of words. We use a modified version of SUMO ontology with greatly extended taxonomy (extended ontology). This extension exists in the framework of developing the "Universal Dictionary of Concepts" (UNLDC) [3]. The extended ontology is an experimental resource and is different from the internal ontology of the linguistic processor ETAP[1] (ETAP ontology), which is also based on SUMO and mentioned further in this paper.

UNLDC translates the concepts of the extended ontology into Russian and several other languages. The Russian lexicon used in this project contains 42,973 Russian words and multi-word expressions with 66,896 senses total. These senses are linked with 48,883 concepts of the extended ontology (both original SUMO concepts and the added ones). UNLDC also has a growing semantic network that includes many relation types not available in the Wordnet, including the cause-result and argument ones. The types of semantic relations supported in this project are described in section 3.2. UNLDC is an open public resource. Its core parts are available for download at GitHub[2]. The extended ontology is a supplement to UNLDC.

3. Knowledge base

Modeling the mechanism of human association reference requires an imitation of human knowledge about the subject domain of the text, which consists of:

a) set of concepts relevant to the domain,

b) semantic relations that hold between such concepts

1 ETAP is a multipurpose linguistic processor developed by the laboratory of computer linguistics at the Institute of Information Transmission Problems (IITP) in Moscow. It supports robust syntactic parsing, English ↔ Russian machine translation, paraphrasing, semantic parsing using two different frameworks, question answering and more.

2 https://github.com/dikonov/Universal-Dictionary-of-Concepts

and an imitation of the relevant subset of human linguistic knowledge sufficient for transition from an NL text to a set of concepts. The latter needs at least chunking and morphology engines to identify sentences and lemmatize words, a semantic lexicon linking the words with concepts and some kind of lexical disambiguation.

3.1. Concept inventory

Using ontology concepts to abstract away from lexical variation and peculiarities of different natural languages always poses the problem of choosing the right degree of abstraction or “semantic grain” for the task. Consider the following example:

(2) Во Владимирской области произошло столкновение товарного *поезда* с застрявшим на переезде *грузовиком*. **Водитель** успел выскочить из кабины. **Машинист** получил травмы.
(A freight *train* hit a *truck* stuck at a crossing in the Vladimir region. The **driver** managed to jump out of the cabin. The **train driver** was injured.)

Bridging is expected to establish relations of association between *машинист (train driver)* and *поезд (train)*, *водитель (driver)* and *грузовик (truck)* based on the fact that each type of driver controls a particular type of vehicle. This information is embedded in definitions of Russian words.

Initially we had three different sets of concepts offered by SUMO, ETAP Ontology and UNLDC to choose from. Straight ontology rendering of this example would use the same class label “SocialRole” (SUMO) / “DriverRole” (Etap Ontology) for the truck and the train drivers. This would not allow the bridging process to see the difference between the two driver entities and link them with the Train and Automobile concepts correctly.

On the other hand, UNLDC uses a very fine-grained set of concepts, that correspond to word senses from several natural languages. In particular, it includes most of the English Wordnet senses. UNLDC concepts can reflect even stylistic distinctions between members of the same Wordnet synset. Semantic classes roughly parallel to NL POS categories are imposed on top. This level of detail is an overkill for most text processing tasks except translation.

The extended ontology offers a fourth option—an optimized set of concepts, more general than lexical senses and more specific than most SUMO/Etap Ontology concepts. It is produced by an automatic procedure. We a) merge into one concept all synonymous senses regardless of the POS class of the source words, e.g. *катание (act of rolling as a ball)* gets merged with *катить (cause to move by turning like a ball)* and all their synonyms b) merge pairs of predicates like *катить (cause to move by turning)* and *катиться (move by turning)*, which differ only by the regular transformation of their argument frames. Each new concept receives a unique OWL-compatible name and a link to an upper SUMO class or another new concept. The new concepts inherit semantic relations from UNLDC semantic network, including *is_a* and *instance_of*, which create subtrees of new concepts within SUMO classes, and other types translated into the bridging relation set, e.g. *катание (roll—act of rolling as a ball)* ^{subProcess} *боулинг (bowling game) = “rolling (balls) is part of playing bowling”*.

3.2. Relations

The relation types supported by our bridging tool are listed in Table 1. This set of relations can be extended through editing of the knowledge base. All relations are directed and have corresponding reverse relation types. Type labels are mostly taken from the Etap Ontology/ Some new ones follow the same style.

Table 1: Bridging relation types

Group	Relation / Reverse relation	Examples (X—Y)	Comment
Function	hasFunction / isFunctionOf	restaurant—serve meals baker—to bake	Y is what X does or is for.
	hasRoleAt / isRoleAt	company—accountant tourists—guide cathedral—priest	Y is a function in respect to the group or object X. There may be multiple persons/objects with the same function.
	hasChief / isChiefOf	team—trainer company—director country—president	The leader of a group
Part ↔ whole	hasPart / isPartOf	room—wall	Parts that are always present
	hasOptionalPart / isOptionalPartOf	room—chandelier	Parts that may be absent
	hasDetachablePart / isDetachablePartOf	lock—key violin—bow	Required accessories that are not physically attached
	hasMember / isMemberOf	parliament—MP government—minister	All members of the group X are Y-s.
	hasSubEvent / isSubEventOf	eat—swallow	
Object ↔ matter	hasIngredient / isIngredientOf	tea—water water—oxygen	Y is one of the raw materials used and irrevocably changed or chemically bound in making X.
	hasSubstance / isSubstanceOf	table—wood ocean—water	X is a mass of pure Y. There may be parts made of other substances.

Group	Relation / Reverse relation	Examples (X—Y)	Comment
Event ↔ role	hasAgent / isAgentOf	buy—buyer fly—airplane	
	hasAgent2 / isAgent2Of	buy—seller	
	hasObject / isObjectOf	write—letter	
	hasInstrument / isInstrumentOf	eat—spoon	
	hasLocation / isLocationOf	study—school	
	hasStartingPlace Point / isStarting PlacePoint	delivery—warehouse (as an order in a webshop)	
	hasTerminalPlace Point / isTerminal PlacePoint	delivery—home (as an order in a webshop)	
	hasRecipient / isRecipientOf	delivery—customer (as an order in a webshop)	
	hasBeneficiary / isBeneficiaryOf	sing—audience	X has an object or message delivered to Y
	hasSource / isSourceOf	passport—Russia	
Cause ↔ result	hasResult / isResultOf	murder—death	
	NewstatusOfAgent / isNewstatus OfAgent	compete—winner compete—looser	Y is a new social role of the agent of the event X
	NewstatusOf Object / isNew statusOfObject	matriculation—student	Y is a new social role of the object of the event X
Temporal	before / after	grab—arrest—jail	Relative position at the timeline. Used in describing typical sequences of events concurrence
	during		Events that occur at the same time but neither is a subEvent of the other
	hasTime / isTimeOf	breakfast—morning	Customary period

Group	Relation / Reverse relation	Examples (X—Y)	Comment
Misc. association	hasResident / isResidentOf	Berlin—Berliner	Resident of a place
	hasBeliever / isBeliefOf	Pope—Christianity socialist—socialism	Supporter and teaching supported
	hasAuthor / isAuthorOf	writer—book	Y is an object designed by X
	hasMaker / isMakerOf	blacksmith—horseshoe	Y is one of many manufactured objects
	hasFrame / isFrameOf	clash—public protest study—university study—seminar	A typical scene (event, institution, proposition) associated with event X and forming its background.
	isUserOf / isUsedBy	woodcutter—ax pilot—airplane	Y is a default instrument of X e.g. an attribute of profession
	hasOwner / isOwnerOf	cop—uniform	X typically possesses Y
	hasAttribute / isAttributeOf	exam—passing grade	
Cohyponyms	cohyponym	hands—legs mother—son	Only usable at low taxonomy levels.

3.3. Domain descriptions

Relations and concepts are used to make semantic graphs containing generalized descriptions of different subject domains. Together such domain descriptions and the extended ontology constitute our knowledge base for bridging.

The graphs consist of triplets, where the relation labels take the place of predicates. A domain description can be saved as an RDF document. Each triplet has an additional annotation field, containing a list of domain names. Domain annotation is used to limit the scope of statements applicable only to certain parts of actual reality.

Domain descriptions are written manually and are later augmented with data from the UNLDC semantic network. Our goal is to cover most domains relevant to everyday life and traditional news topics: shopping, medical care, education, traffic, crime and police, sport, banking, politics etc. They are supposed to model a very basic level of common background knowledge of Russian people, essential to understand contemporary Russian texts, and reflect the reality of Russia and late USSR. The amount of labor needed to describe a single domain is agreeable.

We start by enumerating a few key concepts of the domain (not including any individual persons and institutions). At the next step we link them to each other using the relations from Table 1. Later we enumerate key events concerning the domain and corresponding predicates, e.g. *matriculation, studying, reading, writing, answering, evaluation, passing exams, graduation*, etc. in the educational domain, list their default argument slot fillers, e.g. *student, professor, textbook*, etc, and specify typical temporal and causal relations between the events, e.g. *studying* ^{before} *passing exams*. All this is done ad-hoc to replicate human background knowledge.

The key reason to do it is to capture typical domain-bound sequences of events (scripts) that people follow in their life and work. Scripts are presented as chains of predicate concepts placed along the abstract timeline and connected by the temporal and/or causal relations. A typical scripted activity is fishing where an angler has to *attach (a fly to the hook)* ^{before} *throw (the line into the river)* ^{before} *wait* ^{concurrence} *watch (the cork)* ^{before} *strike (fish)* ^{hasResult} *pull (the line)*, etc. This information is not present in Wordnet or general purpose ontologies, but it turned out to be very useful for bridging. It can explain the relations between participants of the events e.g. *fish* and *cork* by connecting the events they take part in *fish* ^{isAgentOf} *strike* ^{hasResult} *bob* ^{hasAgent} *cork*. UNLDC does provide some cause-result links, but they are limited to universal connections between concepts, embedded in their definitions, e.g. *to grow (vegetables)* ^{hasResult} *growth (of the plants)*.

Another reason is that manually formulated domain descriptions help to identify most important keywords making up the lexical footprint of the domain. We take premade concepts from UNLDC, which already have associated Russian words. Consequently, the domain description graphs are accompanied by a cloud of keywords that help to identify texts domain texts.

The resulting sketch description is immediately useful and can be tested with our bridging tool. We make a test run and check, if there are any important keywords/concepts missing from the domain description. This final step can be repeated many times to improve the recall of bridging relations. The typical size of a domain description is 100–1000 triplets. A fragment is shown in Figure 1.

Domain	Subdomains		Triplet		
EducationalProcess	SchoolEducationalInstitution		SchoolEducationalInstitution	hasChief	Headmaster
EducationalProcess	SchoolEducationalInstitution	Matriculation	OrderRequest	hasAgent	ParentGenitor
EducationalProcess	SchoolEducationalInstitution	Matriculation	OrderRequest	hasRecipient	SchoolEducationalInstitution
EducationalProcess	SchoolEducationalInstitution	Matriculation	OrderRequest	hasRecipient	Headmaster
EducationalProcess	SchoolEducationalInstitution	Matriculation	OrderRequest	hasTopic	ChildJuvenile
EducationalProcess	SchoolEducationalInstitution	Matriculation	OrderRequest	hasResult	Matriculation
EducationalProcess	SchoolEducationalInstitution	Matriculation	Matriculation	hasAgent	ChildJuvenile
EducationalProcess	SchoolEducationalInstitution	Matriculation	Matriculation	hasTerminalPoint	SchoolEducationalInstitution
EducationalProcess	SchoolEducationalInstitution	Matriculation	Matriculation	hasResult	EnrollRegister
EducationalProcess	SchoolEducationalInstitution	Matriculation	EnrollRegister	hasAgent	SchoolEducationalInstitution
EducationalProcess	SchoolEducationalInstitution	Matriculation	EnrollRegister	hasObject	ChildJuvenile
EducationalProcess	SchoolEducationalInstitution	Matriculation	EnrollRegister	NewstatusOfObject	Schoolchild

Figure 1: A few lines of a domain description showing the process of enrolling a child in a school. "The parents make an application to the school. The child gets enrolled and becomes a pupil"

The domains have their own taxonomy. Statements made in the general domains, such as *Education* and *Shopping* apply together with all statements from more specific domains, such as *University* and *Supermarket*.

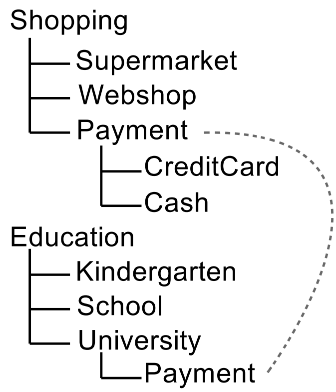

Figure 2: A fragment of the taxonomy of domains

All relations in the knowledge base describe a default general state of affairs within a specified domain. The statements made in the domain descriptions are just "usually true". No claim for universal truth can be made here. Actual truth in the real world or a fictional reality described in some concrete text has to be determined during understanding of the text or a situation in the real world. For example, the *TerminalPlacePoint* argument slot of the concept *Carrying* is always filled by some *Region*. The statement *Carrying* ^{hasTerminalPlacePoint} *Region* is universally true. However, in the domain of supermarkets shoppers usually carry goods to the checkout counter. Therefore, the description of the supermarket domain contains the statement *Carrying* ^{hasTerminalPlacePoint} *Checkout*, which is expected to be true in the domain. It makes the content of the domain descriptions unfit for a general purpose ontology, where all statements must be universally true. Instead each sub-domain section of a domain description could be viewed a small domain ontology.

4. Bridging annotation

Our bridging annotation tool has two major options. One is to search through a corpus and detect fragments of text that match known domains. The other is to generate a set of potential bridging relations for the fragments.

We use a corpus of newspaper texts as a source of examples. It consists of automatically parsed news feeds and full articles in the ETAP TGT format. The current version of the program ignores syntax structures and uses only lemma tags. It also supports ETAP combinatorial dictionary entries for disambiguation and falls back to lemmas if they are not available. A simple TF-IDF ranked keyword search is used to extract fragments that contain higher than average density of keywords linked with available domain descriptions. The length of the fragments is not set and usually falls between 3 and 15 sentences. Each fragment gets tagged with the applicable domains with weight numbers. There is a weigh threshold which can be adjusted to tune the output between better domain detection and quantity of examples.

The current bridging annotation option works as follows: an example text is scanned for any nouns and verbs listed in UNLDC. They are taken in the linear order of the text and paired with every preceding word mentioned in the UNLDC Russian lexicon in turn. The candidate pairs of words are turned into two sets of concepts, associated with different senses of both words. The concepts linked with the possible reference word and mentioned in the background knowledge base are paired with all concepts linked with the possible antecedent.

Resulting pairs of concepts are fed to a search function which returns all possible bridges between them, if any. The bridges may consist of either a single semantic relation or a chain of 1–2 intermediate concepts with relations between them. Since the extended ontology has taxonomic relations between its extra concepts within SUMO/Etap Ontology classes, the search function can use subclass_superclass_sibling criterion [4] to improve recall and relate antecedent concepts not mentioned in the domain description.

A sorting function selects the most probable bridges by weighting them according to such criteria as number of intermediate concepts ("bridge arks"), number of assumed extra concepts, distance between the reference and antecedent, saliency, etc. Each confirmed antecedent word receives a list of discovered reference words and clusters of bridge links are formed.

An interesting feature of our tool is building of a possible associations list. Intermediate concepts, which are not linked with any words in the text but occur in complex bridge relation, e.g. *Policeman* in Example 1, are remembered. Most frequent associations are returned together with the list of discovered bridging pairs.

5. Problems and limitations

Like every other ontology based system, our approach falls prey to the expert knowledge input bottleneck. The amount of background knowledge provided by domain descriptions is never enough (just like with us humans) but extending them manually is a labor intensive process that gets harder with more elaborate descriptions.

The tool demonstrates domain bias. Lack of a relevant domain description provokes our tool to switch to other domains which have partially similar lexical footprint. As a result, news reports about politics and wars, for instance, get interpreted in terms of crimes and terrorism. Sport events can get mixed with theater performances because both actors and athletes play and win contests and those domains share a certain amount of keywords. This problem can be mitigated by making brief descriptions of interfering domains that cover problematic keywords.

There is a whole range of different problems that cause generation of excessive bridging relations, which are either redundant or the contents of the text logically overthrows them. Some of them are described below.

Use of very general ontology classes in domain descriptions creates spurious assumptions, yet it is hard to avoid. For example, the domain of police work includes the concept of arresting some *Human*. It makes the system assume that every entity of a *Policeman* arrests every entity of a *Human* mentioned in the text. It is impossible to enumerate all possible objects of arresting.

The system can make bridges that are irrelevant or redundant from a human point of view. For example, it can link words *зачетка (student's grade book)* and *дверь (door)*: *grade book* ^{hasOwner} *student* ^{isAgentOf} *opening* ^{hasObject} *door.*

There is no good stopping rule in assumption generation, except to ban all concepts not explicitly mentioned in the text. In a story about hijacking of a car that results in a chase, crash and explosion, the computer will happily (mis-)assume an existence of a bomb and some terrorists, because the bag of concepts (*Automobile, Impacting, Explosion, Policeman, Criminal*) has enough similarity with the domain of terrorism. This problem can also affect humans, when there is no sufficient context to rule out wrong assumptions.

It is really hard to make a filter that would remove such unwanted relations. The software tool and KB described in this paper do not represent a complete model of text understanding. They simulate recalling background knowledge and associating concepts previously derived from the text (given information) with new concepts encountered while reading. The system does not implement logical judgment of the resulting associations. The generated bridging relations can either be true in the realm of the analyzed text or be irrelevant. In order to match human judgment, every proposed bridging relation must be evaluated using very high-level semantic criteria. Such evaluation presupposes a) full anaphora resolution to produce a list of mentioned entities with lists of words used to refer to them in the source text, b) full semantic parsing and, possibly, complex reasoning on top to determine the relations between the entities already stated in the text. The following example contains two different entities of retail stores. One is a part of the named retail chain, the other is not.

(3) …откроется новый *магазин* **сети** X5 Retail. Располагаться он будет на месте бывшего **супермаркета** «Окей-Экспресс».
…a new *store* of the X5 Retail **chain** will open. It is located in the place of the former "OK-Express" **supermarket**.

Our current program is designed to process a minimally tagged corpus[3] without a semantic parse. It must propose the relation *("OK-Express") supermarket* ^{isPartOf} *chain ("X5 Retail")* because it has no means to discover that it is wrong. Other bridging projects also have this limitation and resort to various heuristic rules to reduce the amount of irrelevant bridges.

6. Evaluation

Evaluation by using the traditional precision/recall measurement against a manually tagged test corpus proved to be impractical in this case. The very nature of the modeled process implies high variability and individual bias.

[3] It contains lemmas (or ETAP lexemes) and morphological tagging. Optionally, syntactic relations could be used to remove bridging relations that would duplicate existing syntactic relations.

6.1. Test data

A pilot sample of a test corpus was made and tagged by 6 annotators. The test consists of two short texts, 2,627 words in total. We tried to follow formal rules similar to the ones implemented in the software, but applied human reasoning to select bridges relevant for understanding the text. The result clearly demonstrated that each annotator saw a different set of associations. The inter-annotator agreement was so bad that we rejected the idea of making a larger corpus. Out of 197 unique pairs of reference+antecedent words in the test material only 1 pair was universally accepted by all annotators and 148 pairs (75.1%) were chosen by only one person. Table 2 provides an overview.

Table 2: Percentage of detected bridges vs number of annotators sharing them

Annotators	1	2	3	4	5	6
Pairs %	75.1%	13.2%	7.1%	3%	1%	0.5%

In most cases when several annotators selected the same bridging pair with a semantically complex relation, they interpreted it differently. For example, three annotators expressed the relation between *покупатель (buyer)* and *магазин (store)* in the following three different ways: *1) buyer* ^{hasLocation} *store*, 2) *buyer* ^{isAgentOf} *buying* ^{hasFrame} *store*, 3) *buyer* ^{isRecipientOf} *retailing* ^{isFunctionOf} *store*. All three variants are acceptable.

The detection of words that represent reference and antecedent entities in the texts was much more uniform with 59% of the words chosen by at least 3 annotators and 44% chosen by more than 3 people.

This situation is well aligned with the theory of bridging explained in section 1. The Listener produces associations based on his unique background knowledge, prior information and current goals. Every instance of understanding, even by the same person, may follow a different path of associations. It is unrealistic to expect that several people will produce identical sets of bridging links.

6.2. Result

The same two texts were fed to our bridging program which produced 532 candidate bridging relations. Comparison between the collective of human annotators and our system shows that the computer was able to tag 78 (39.5%) out of 197 referent+antecedent word pairs tagged by at least one human annotator. It compares favorably against the numbers of bridges found by each single human. Table 3 shows individual recall of human annotators and the computer.

Table 3: Number of detected bridges per annotator out of the total pool of 197 relevant pairs

Annotators	A	B	C	D	E	F	Computer
Pairs	22	23	35	46	72	84	**78**
%	11.1%	11.6%	17.7%	23.3%	36.5%	42.6%	**39.5%**

Only one of the annotators managed to find more bridges than the system. All semantic labels ascribed by the computer to the 78 detected bridging relations were correct, even when they were different from manually crafted types of “multi-arc” bridges. The overall demonstrated recall is lowered by temporary limitations of the software, such as lack of support for named entities, and has a potential to be improved.

7. Conclusion

We develop a semantic knowledge base geared towards bridging resolution. It opens up a possibility to explore semantic approaches in Russian and use richer background information than previous studies. All established bridging relations receive a semantic interpretation, which is not limited by a fixed set of pre-defined labels. Flexibility granted by combining multiple relations and intermediate concepts in “multi-arc” bridges allows to represent complex associations but creates problems mentioned in sections 5 and 6. Bridging relations are important for discourse analysis because they link distant, but semantically related parts of text and explicate their cohesion.

The results of this work are supposed to be used to improve the semantic parser of the ETAP system [1], if it proves to be viable. It is also worth to explore the possibilities of population the domain descriptions and ranking plausibility of different alternative antecedents by ML.

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