

Modeling Russian Verbs of Motion: An Analogical Account

Inna Danielyan Dodge (innadan@byu.edu)

Department of Linguistics and English Language; 4039 JFSB
Provo, UT 84602 USA

Deryle Lonsdale (lonz@byu.edu)

Department of Linguistics and English Language; 4039 JFSB
Provo, UT 84602 USA

Abstract

This paper presents research into verb of motion (VOM) constructions in Russian. These constructions are difficult since they involve (i) selection of an appropriate verb (with possible prefixation); (ii) selection of an appropriate preposition; and (iii) selection of an appropriate case for marking the prepositional object. A brief sketch of relevant literature frames the problem. We then discuss how a few thousand instances of VOM usage were extracted from an online tagged corpus of Russian literature. The usage instances were then vectorized using a combination of lexical and semantic class features via automatic, semiautomatic, and hand-coded methods. The instance base was then processed via the analogical modeling paradigm to account for predictability of the case, the preposition, and both simultaneously. Discussion of the results and possible future research directions then follows.

Keywords: Russian; verbs of motion; analogical modeling; morphosemantics.

Introduction

A complex and challenging facet of the Russian language is the group of verbs variably referred to as verbs of motion, location, or transport (hereafter VOM's). The simple English sentence "*He brought me to his house.*" may be rendered into Russian differently depending on the conveyance used (or absence thereof), means of displacement (e.g. by foot or by vehicle), the vectoriality or directionality, and the perfectivity (degree of completion) of the event in question. VOM constructions typically have four relevant core parts: a subject, a VOM, a preposition, and a prepositional object. The VOM may be conjugated for tense and inflected (e.g. via a prefix) for aspect. The prepositional object is inflected appropriately for case (usually with suffixes). Selection of which verb and which preposition to use in a given instance, as well as the case marking on the prepositional object, is a difficult task that involves re-expressing the target situation via a grammatically correct VOM construction.

This research focuses on functional relations between verbs of motion (unprefixed and prefixed) and their nominal arguments with relevant case markings. We consider 14 pairs of VOM's in all of their possible prefixed and conjugated forms. We also describe a set of semantic features for describing their aspectual, syntagmatic, and spatial/directional properties, and how we use these features for language modeling.

In this paper we address the question of modeling VOM constructions by using a corpus-derived exemplar base and

a machine learning system called analogical modeling (Skousen, Lonsdale, & Parkinson, 2002). The system analyzes data instances based on a set of lexical and semantic features. Through a process of analogy it eliminates all the inconsistent (heterogeneous) outcomes and chooses the most analogous result for the given context.

Usage instances were extracted from an online corpus, encoded as feature vectors, and tested for prediction of correct prepositions in verb of motion phrases based on the semantic features of the verbs, their prefixes, and objects with relevant case markings. We illustrate how the process of analogy in AM serves to predict the choice of the preposition in VOM phrases on the basis of the semantic features of the verbs and their nominal arguments with relevant case markings.

Background

Even native speakers of Russian occasionally produce certain types of case errors (Demidenko, 1986) including those involving the prepositional case, which is often used in VOM's. Less unexpected is the fact that learners of Russian as a second language show several difficulties in acquiring Russian case (Rubinstein, 1995). This research confirms our personal observation that non-native learners of Russian often confuse the accusative case with the prepositional.

A limited amount of pedagogical material exists for VOM's (Mahota, 1996); the topic is apparently underexplored in the Russian linguistic literature (though see (Muravyova, 1986)). It would appear that more work in this area has done by Western linguists (Titelbaum, 1972; Pahomov, 1977; Vaimberg, 1981; Launer, 1987)). Still, to our knowledge, no work has focused on language modeling and Russian (or any other Slavic language's) verbs of motion. In this paper, we use AM to study relevant aspects of this construction.

In this paper we adopt a standard set¹ of fourteen VOM's (Karcevski, 1927; Muravyova, 1986; Andrews, Averyanova, & Pyadusova, 1997), plus their conjugations.

One distinction that is pertinent for these verbs involves their indeterminate/determinate status. Determinate verbs have a single appreciable vectoriality or directionality; indeterminate ones are repeated, habitual, autonomous, or unspecified for space or time. The determinate verbs are considered marked and hence non-default.

Each of the verbs can acquire about 17 prefixes, primarily spatial/directional in nature. When this happens, the (in)determinate dichotomy disappears. Other effects arise;

¹Various researchers have developed slightly different sets of VOM's.

<i>Intransitive verbs of motion</i>		
Indeterminate	Determinate	Gloss
ходить	идти	to go on foot, to walk
ездить	ехать	to go by means of transport, conveyance
бегать	бежать	to run
летать	лететь	to fly
плавать	плыть	to swim, to sail
ползать	ползти	to crawl
бродить	бродить	to wander, to roam
лазить	лезть	to climb
<i>Transitive verbs of motion</i>		
Indeterminate	Determinate	Gloss
гонять	гнать	to chase, to drive
катать	катить	to roll, to push on wheels
носить	нести	to carry, to take by hand
таскать	тащить	to drag, to pull
водить	вести	to lead, to take on foot
возить	везти	to transport, to take by transport

Figure 1: Infinitival forms of Russian verbs of motion.

for example, both types of verbs, when prefixed, can become perfective. A listing of the possible VOM categories is given in Figure 2.

Unprefixed		Prefixed	
Imperf.		Perf.	
Indeterm.	Determ.	Indeterm.	Determ.

Figure 2: Partial hierarchy of verbs of motion

This raises an interesting issue: is there a hierarchical relationship between these components? If so, which determine the choice of the others, and what is their relative importance? The usual and traditional claim is that the preposition governs the choice of case marking for its object, though this has been challenged (Whibley, 1982; Bethin, 1983). We thus believe that the topic is germane for exploration.

Several different language modeling paradigms have served to investigate language use. Connectionist, rule-based, memory-based, statistical, competition-based, and information-theoretical accounts have been advanced for different language-specific and crosslinguistic phenomena. To our knowledge no modeling work has been done in Russian VOM's in any of these frameworks. Similarly, no detailed theoretical accounts of cognitive processing—whether psychologically plausible or not—have yet addressed the use of VOM's. Our intent here is to at least initiate work in this area; we seek to benchmark the exploration of the complexities involved in Russian VOM's and to raise relevant issues. In this effort we adopt one established paradigm of language use modeling: analogical modeling (AM). While cross-paradigm comparisons could naturally follow from this work, we restrict this description to our efforts within AM.

Analogical modeling (AM) is a symbolic exemplar-based language modeling paradigm that establishes analogical comparisons between a set of instance data and test items, each

represented as a feature vector² (Skousen, 2002). The data instances represent exemplars of separate linguistic usages. Each test item is systematically evaluated against the data instances in order to predict its appropriate outcome. Not all features need be fully specified; some may be absent or erroneous, thus representing partial or noisy data.

From a vector of n test item features, we choose m (where $0 < m \leq n$) specified features (i.e. a subset thereof) and test them against the data instances for similarity. These so-called supracontexts (of which there are 2^m) can be categorized as being heterogeneous or homogeneous based on whether their subcontexts all behave identically (i.e. have the same outcome). Only results from homogeneous supracontexts are kept; the other contexts are discarded. The analogical character of the approach lies in measuring the disagreements among the outcomes associated with these feature subsets. In particular, a homogeneous supracontext has no subcontext that increases this number of disagreements.

For a given test item, only two types of homogeneous contexts can exist: (i) deterministic supracontexts with only one outcome, and (ii) nondeterministic contexts where all occurrences are equidistant from the test item. The “analogical set” combines these two types of homogeneous supracontexts. The system chooses one of the outcomes from this analogical set as the outcome for the test item in question; the choice can either be done randomly, or else by plurality (i.e. the most frequent outcome). Based on this notion of similarity, analogs often—but not always—correspond to nearest neighbors; regular items further away can sometimes conspire together in “gangs” to affect the outcome. Various parameters control such phenomena as imperfect memory and frequency effects; hooks into the core engine allow for visibility into and interaction with the algorithm's operations.

²We should note that we use the term “vector” throughout, though in fact the features are purely discrete and symbolic; they are not continuous-valued or numeric.

AM has been successfully applied to a wide range of linguistic phenomena, though primarily in the lexical, phonological, and morphological realms. The semantic realm is relatively unexplored in the paradigm³, and this paper addresses semantic phenomena within this approach. Detailed analyses are available elsewhere of the analogical procedure itself (Skousen, 1992), its application to language modeling problems (Skousen, 1989), and its algorithmic implementations (Skousen et al., 2002).

Methodology

In this section we discuss how the data instances were collected, how they were mapped to an appropriate feature vector representation, and then how they were processed by the AM system.

Instance collection

The exemplar base for this research was built from several thousand instances of VOM constructions extracted from the Tübingen online corpus⁴. The corpus consists of a morphologically tagged collection of literary texts, newspaper articles, and magazine articles.

A one-sentence context was retrieved from all available corpora for each verb form using a regular expression. For example, the verb *подойти*, “to approach, come up, walk up by foot” in its infinitive and past tense forms produced 415 instances of tagged sentences, such as the extracted example below⁵:

```
Bazarov/substantiv_masc_pl_gen_unb
vstal/verb_finit_prt_0_sg_masc_nref_pf
i/konj_koor
podoshel/verb_finit_prt_0_sg_masc_nref_pf
k/praep_dat
oknu/substantiv_neut_sg_dat_unb
./satzzeichen_punkt
```

meaning “*Bazarov got up and walked up to the window.*”

Feature encoding

Once the instances were retrieved from the corpus, a Perl program then extracted from each sentential context the four lexical features that participate in VOM constructions.

The following information was thus extracted for our example sentence:

```
k_dat, bazarov podoshel k oknu
```

So far, then, the features consist of: (i) the outcome *k_dat*, meaning that the VOM has the preposition *k* and is dative; and (ii) four lexical features or variables *bazarov podoshel k oknu*, representing the subject of the sentence, the verb of motion, the preposition and the case-marked prepositional object.

Several points regarding these lexical features are worthy of mention:

³though see the discussion on Arabic lexical selection in (Skousen, 1989)

⁴See www.sfb441.uni-tuebingen.de/bl/en/korpora.html.

⁵We adopt the fairly idiosyncratic Romanization scheme used in the corpus for our data representations and hence our examples in this paper.

- Russian is a *pro-drop* language, meaning that the subject is optional and hence often missing in the exemplar sentences.
- Only VOM’s listed in Figure 1, along with their various conjugations, were extracted.
- There are forty-three prepositions and thirteen further variant forms (i.e. allomorphs) of these in the exemplar base. In this work we did not collapse them, thus incurring a slight reduction in accuracy in the system’s performance.
- The Russian case paradigm consists of six cases, namely: nominative, genitive (*gen*), dative (*dat*), accusative (*akk*), instrumental (*ins*), and prepositional (*prp*). Only the last five cases appear in the outcomes; nominative marks subjects and hence can never mark prepositional objects.
- Some prepositions occur with various cases: the prepositions *в* “in, into” and *на* “on, onto” are shared by accusative and prepositional, *за* “for, behind” is shared by accusative and instrumental, the preposition *с* “with, off, approximately” is used with instrumental, genitive and accusative, and so on.
- The Perl lexical feature extractor did not always correctly process some corpus instances, so occasional incorrect subjects or objects resulted. This presence of errors in the input data is in fact interesting since it reflects the fact that real language data is indeed inherently noisy to a language learner, and also since AM is robust enough to deal with such data.
- Some incorrect case tagging was found in the corpus. For example, *za_dat for, behind_dative* is impossible in Russian, as were other forms we encountered in the corpus: *v_akk* encoded as *v_prp* and vice versa.

We then added semantic features manually to each feature vector, based on the semantics of the VOM construction. The features we chose were based upon Frawley’s claims about the universality of his spatial concept definitions (Frawley, 1992). He distinguishes two kinds of locations encoded by language: topological (i.e. objective) locations and projective (i.e. subjective) locations (see Figure 3). Our choice, of course, is not meant to be all-encompassing of the problem and is somewhat prescient since it is conditioned on our existing knowledge of the language, so our feature set cannot be taken as a complete necessary and sufficient specification of the features required for this task. It is rather an opportunistic leveraging of pre-existing work in this area.

After adding these semantic encodings our sample vector is as follows:

```
k_dat, v y o l bazarov podoshel k oknu
```

Here we see the four semantic features prepended to the lexical ones described above. The first three semantic features belong to the verb of motion *пошел* “came up by foot, approached”, and the last letter represents a semantic feature of the object *окно* “window”. Here the letter *v* stands for intransitive, *y* for determinate, *o* for “by foot: regular speed”, and *l* means laterality. See Figure 4 for a further explanation of the semantic features and Figure 5 for sample instance vectors.

<i>Topological</i>	
Coincident	The fly is on the wall.
Interior	The books are in the box.
Exterior	The ball is out of the box.
<i>Projective</i>	
Inferior	The cat is below the table.
Superior	The shelf is above the table.
Anterior	The spoon is in front of the pumpkin.
Posterior	The pumpkin is behind the spoon.
Lateral	Donna is beside the car.

Figure 3: Semantic features from (Frawley, 1992)

bez_gen, v y o i ego vojti bez predstavlenij,
dlja_gen, v y h i ja priexala dlja toho,
do_gen, v y o a zhelaniya doйти do cherty,
izo_gen, v y o e nogi vyshla izo rta,
k_dat, v y o l zvengey idet k paraskeve,
k_prp, v q o l cypochkax podxodit k dveri,
mimo_gen, v y o l vse projdet mimo shkoly,
na_akk, v y o c a vyshla na ulicu,
na_prp, v y h c zhizni exala na letuchke,
o_prp, z y a i vernoj vesti o smerti,
ob_akk, v y o ? vymyvanie idut ob prakticheski,
okolo_gen, v y o ? pgesa proshla okolo raz,
ot_gen, v y o e bankovskij ujti ot melochnogo,
po_akk, v q o i vse xoditq po griby,
po_dat, v q o c arapy vxodjat po trapu,
po_prp, v y o c on shel po tropke,
pod_akk, z y a f ee vesti pod ruku,
posle_gen, v y o p oni ushli posle akta,
pri_prp, z y a l zhivyx vyveli pri ehtom,
pro_akk, z y a ? ehtogo vyvela pro shilku,
protiv_gen, v y o l vy idete protiv naroda,
putem_gen, v y o i rudin doshel putem filosofii,
s_akk, v y o i my proshli s chetvertq,
s_gen, v y o i my proshli s chetvertq
s_ins, v q o i schastlivoe prixodit s glotkom,
sredi_gen, v q o l my xodim sredi palatok,
v_akk, z q a n kotoroe vvoditq v dom,
v_prp, v y h n vysokoj vyexala v triko,
za_ins, v q o i ty xodil za doktorom,

Figure 5: Sample instance vectors.

<i>Feature 1</i>	
Intransitive/transitive	v/z
<i>Feature 2</i>	
Indeterminate/determinate	q/y
<i>Feature 3</i>	
Foot: regular_speed/slow/fast	o/w/b
Arms & legs: ground/into/air/water	u/g/r/m
Vehicle: car/plane/ship	h/x/j
Coincidence: slow	k
<i>Feature 4</i>	
Features from Figure 2, plus:	
Completely: through	t
Direction	d
Instrument/benefactive	i
Superiority	s
<i>All features</i>	
Don't know	?

Figure 4: Semantic features used in instance vectorization.

Running the system

The analogical modeling system takes two input files: the data file of instance (or example or exemplar) vectors, and the test file, consisting of similarly vectorized queries to the system. Each test item is compared to the input instances, analogies are computed, outcomes are scored, and a report is output. Several parameters can be controlled during processing via a Perl wrapper to the basic underlying system. For example, a threshold can limit what percent of the input data should be randomly selected for processing, precluding the rest. In addition, instances of the test items in the input data can be included in processing (resulting in simple retrieval of their outcome) or excluded from processing if they also occur in the input data (hence forcing analogical processing to take place). In fact, a common experimental condition is to exclude the givens.

A report for each test item illustrates which outcomes are possible, and gives a percentage weight for each. Figure 6 shows part of a listing of results with slightly different features than those described above. The first instance was correctly guessed with a confidence of 100%. The second instance was incorrectly guessed to be *v_akk* when in fact it should have been *cherez_akk*, and so on.

The system can be run to predict either the preposition-case combination simultaneously, or the preposition first and then the case, or vice versa.

Results and discussion

Several different feature combinations were tried with the full data set described above. All tests were done in leave-one-out fashion, testing each item from the data set in turn against the full data set (minus any occurrences of the item in question).

```

Test:  akk v y o t skvoznym idut galerei,
If context is in data file then exclude
Statistical Summary

cherez_akk      16  100.000%
--
16

Expected outcome: cherez_akk
Correct outcome predicted.

Test:  akk v q o t solomin perexodil komnatu,
If context is in data file then exclude
Statistical Summary

cherez_akk      624   37.321%
skvozq_akk      168   10.048%
v_akk           880   52.632%
----
1672

Expected outcome: cherez_akk
Incorrect outcome predicted.

Test:  akk v y o t strana proshla ispytaniya,
If context is in data file then exclude
Statistical Summary

cherez_akk      16   66.667%
k_dat           8   33.333%
--
24

Expected outcome: cherez_akk
Correct outcome predicted.

Test:  akk v q o t svet proxodit atmosferu,
If context is in data file then exclude
Statistical Summary

cherez_akk      240   59.553%
k_dat           1    0.248%
skvozq_akk      160   39.702%
za_akk          2    0.496%
---
403

Expected outcome: cherez_akk
Correct outcome predicted.

```

Figure 6: Sample output from the system.

We first tested the system using only the lexical features. When three features were tried (i.e. excluding the preposition), a 44.19% score was obtained. This low score is not too surprising since the lexical forms themselves are merely symbolic tokens that can only be compared via direct equality/inequality tests.

On the other hand, adding the fourth lexical feature, the preposition, to each instance upped the score considerably to 83.74% correct. This is an understandably high result since once the preposition is known the only decision left is to choose the relevant case.

On the other hand, adding case (but not the preposition) to the three lexical features on the input vectors, and thus forcing the system to guess the preposition, only yielded a score of 67.32%. Clearly the system had more trouble predicting the preposition than predicting the case. This, too, is understandable since there are more possible preposition outcomes (43) than case outcomes (5).

We next tested the hypothesis that the semantic features of verbs of motion and their nominal arguments with relevant case markings will help in predicting the choice of the preposition. To do this, we ran the data set whose instances all had the additional four semantic features. When guessing the case given the preposition, the system scored 89.2% correct, an improvement of 5.46% over similar runs with only lexical features.

A further question arises: is it easier for the program to guess the preposition-case combination simultaneously or would it be more efficient to guess the preposition first and then the case and vice versa? Does the case of the nominal argument depend of the preposition or on the verb of motion? Does the preposition depend on the nominal argument with its relevant marking or on the verb of motion?

To force simultaneous preposition/case guessing, both the prepositional and case features were excluded from the vectors. AM scored a very low 13% This remarkably poor result (verses the score of 44.19% using only three lexical features) shows the effect of added complexity given the four new semantic features. Both trials, though, demonstrate the difficulty of guessing the preposition and the case simultaneously.

We also tested the third option—guessing the preposition given the case. In this the system scored a reasonable 86%. Based on these scores, it can be concluded that, based on the feature set we implemented, it is more difficult to simultaneously select the appropriate preposition/case VOM combinations than it is to have a staged decision process. The two-step treatment of VOM constructions as a preferential production strategy also meshes well with current pedagogical practice, based on the first author's personal teaching experience, and confirms the challenging nature of simultaneous guessing.

A ranking of the relative strength of the features using TiMBL's gain ratios (Daelemans, Zavrel, Sloot, & Bosch, 2003) showed that the relative importance of the features was (in decreasing order): (1) the semantic feature of prepositional object; (2) the transitivity/intransitivity of the VOM; (3) the object's lexical form; (4) specific semantic feature of the verb of motion (e.g. foot: regular speed or vehicle: car, arms and legs etc.) (5) the indeterminate/determinate status of the verb of motion; (6) the preposition itself, when present; and (7) the verb of motion itself, the only lexical feature.

One interesting aspect of AM is its ability to model human errors. Leakage occurs when one outcome is favored over another when errors are produced (Skousen, 1989). For example, the production of *a versus an* in English favors leakage towards the former; “*a apple*” is more likely to be heard than “*an telephone*”.

Consider the summary of the distribution of results for all 1108 items having the outcome *v_akk*:

```
Test items with outcome v_akk
0.090% k_dat (1/1108)
0.090% na_akk (1/1108)
0.090% na_prp (1/1108)
0.090% o_prp (1/1108)
0.090% s_gen (1/1108)
97.022% v_akk (1075/1108)
2.527% v_prp (28/1108)
```

The correct outcome *na_akk* was almost always guessed. However, the system also demonstrates slight leakage towards *v_prp* as the second choice, thus exhibiting a confusion similar to that of learners as they acquire Russian.

Future work and possible applications

This preliminary work is promising and several further directions for future research are possible.

Of course, a larger dataset would be useful for more thorough testing of the hypothesis. Other tagged corpora would be necessary for this effort, or alternatively more work on our part to identify, tag, and extract contexts of interest from other sources.

We also envision adding more semantic features to the instance vectors. For example, though prefixes play a crucial part in VOM's, we did not encode any prefixation information into the vectors. It is unclear at this point whether such features would serve to complicate the problem or instead to add more information to that would be helpful in determining outcomes.

We would like to have a more automatic way of encoding the semantic features, perhaps by using some lexico-semantic resource that could provide such information.

It would also be interesting to conduct a study involving human subjects and their second-language acquisition of Russian VOM's, including errors, in order to arrive at a more thorough account of cognition in VOM's. The participants would be given the same task of predicting prepositions based on the semantic features of verbs of motion and nominal arguments with their relevant case markings. Then the results from this and previous acquisition data would be compared to the AM outcomes in order to draw analogies between language modeling and human acquisition of language.

We recognize without reserve that other cognitive frameworks beyond AM have the potential for addressing these same phenomena. For example, since we have cast the issues in this paper as a categorization problem, several alternative approaches exist, for example statistical, causal, or entropy-based. Each warrants further investigation.

We could perform a more thorough version of the testing using tests for statistical significance and precision/recall measures so that the results are more directly commensurate with comparable investigations of similar phenomena in the literature. These types of testing regimes have yet to be done within the AM research paradigm, so such work would be

even be helpful from a methodological standpoint, setting aside the linguistic issues. Further research could also investigate the problem under other machine learning approaches (e.g. TiMBL or decision trees), comparing and contrasting the results of the various approaches.

Finally, possible applications of this research can be used in developing Russian language learning software and computerized Russian text processing.

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