Identifying and Quantifying Aspectual Ambiguity with LMs

Reversing the NLP Pipeline

Bachelor Thesis

Date, Year

Samuel Innes

innes@cl.uni-heidelberg.de

Institut für Computerlinguistik

Ruprecht-Karls-Universität Heidelberg

Supervisor Prof. Dr. Michael Herweg

Reviewer Prof. Dr. Katja Markert

Abstract

Abstract in English

Zusammenfassung

Zusammenfasssung auf Deutsch

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1 Introduction

Motivation

Despite being one of the most studied areas in linguistics, I COULDNT FIND ANY statistical approaches to aspect.

It also serves/aims??? to be a case study in the use of Language Models in linguistic research.

Why aspect?

One may justifiably beg the question why a "computational approach" to aspect (OR INDEED TO ANY PROBLEM IN THEORETICAL LINGUISTICS) is necessary or indeed useful: in an age of LLMs

The use of such a study comes down to the purpose of computational linguistics as an area of study. Computational linguistics has changed a lot since its conception in the mid 20th century, at some points being closer to linguistics and at others (arguably including right now) being closer to computer science. However the position of the field lying at the intersection between more well-established and well-defined areas of study has led to a fruitful exchange of ideas between the disciplines.[1]

One reason is of course the contribution to the linguistic community: computational approaches to language have SPURRED ON LOTS OF PROGRESS (cf Chomsky!!!). A

In the true nature of the interdisciplinarity of the field I wish to WORK AT BOTH AIMS IN PARALLEL and show how they complement each other.

Importance on engineering side:

- Zero-shot performance of ChatGPT comparable with BERT [Zhong et al., 2023]

[1] Just to name a few examples: formal languages, artificial neural networks and SOMETHING ELSE!!!!!!

- I also experienced poor (?) performance with own experiments
- but fine-tuning lead to large improvements
- UMR annotates aspect, and this can be used to extract habitual events or states, which are typical knowledge forms

The fact that fine-tuning can lead the model to

Therefore the purpose of this study is two-fold: firstly to further explore the phenomenology of aspect using methods from computational linguistics such as neural embeddings, and secondly to look at how current state-of-the-art approaches deal with this phenomenon and investigate how this could be improved.

I wish to challenge Chomsky's assertion that large language models are "not a contribution to science"[2]

Main contributions

- First in-depth study using computational approaches to study the phenomenology of aspect
- First probing of neural models applied to the task
- SOMETHING ELSE

Structure of this thesis

Acknowledgements

Valentin Dad

[2] https://www.youtube.com/watch?v=axuGfh4UR9Q WHAT TIME DOES HE SAY THIS???

2 Aspectology: an introduction

Many works on the area begin with the assertion that aspect is one of the most studied areas of linguistics [Sasse, 2002], particularly Slavic linguistics (for reasons I will discuss later), and hence a thorough theoretical discussion of the linguistic phenomenon which does full justice to the work on the field is not possible within the constraints of this thesis. Nevertheless, in order to give an introduction to the fundamental elements of the following study and make a productive contribution to the area, I will touch on some of the main findings in the area of aspectology.

2.1 A (short) phenomenology of aspect

The Concise Oxford Dictionary of Linguistics [Matthews, 2014] defines aspect thus:

> [Aspect is a g]eneral term, originally of specialists in Slavic languages, for verbal categories that distinguish the status of events, etc. in relation to specific periods of time, as opposed to their simple location in the present, past, or future.

As noted here, one helpful distinction which must be made right away is that between *aspect*, and another temporal phenomenon *tense*. Many works recall Bernard Comrie's differentiation in his book *Aspect* [Comrie, 1976] between the deictic nature of *tense* and the focus on the "internal temporal constituency of a situation" of *aspect*. In other words: "tense[1] relates the time of the situation referred to to some other time, usually to the moment of speaking", and thus by relating the time of the situation to the time of the utterance it is deictic [Comrie, 1976]. Aspect on the other hand gives a *situation-internal* description of the events in that situation, such how they relate to each other temporally or how an individual event is temporally characterised. This introduces another important distinction: that between lexical and grammatical aspect.

[1] In many of the world's languages this is grammaticalised as past, present and future; in others such as English by some accounts [Jespersen, 1933] it is a binary distinction such as past and non-past, whereas some languages such as Greenlandic (Kalaallisut) some linguists have even argued to be tenseless Bittner [2005]. See also the contentious debate about Hopi time Whorf [2012], Malotki [1983].

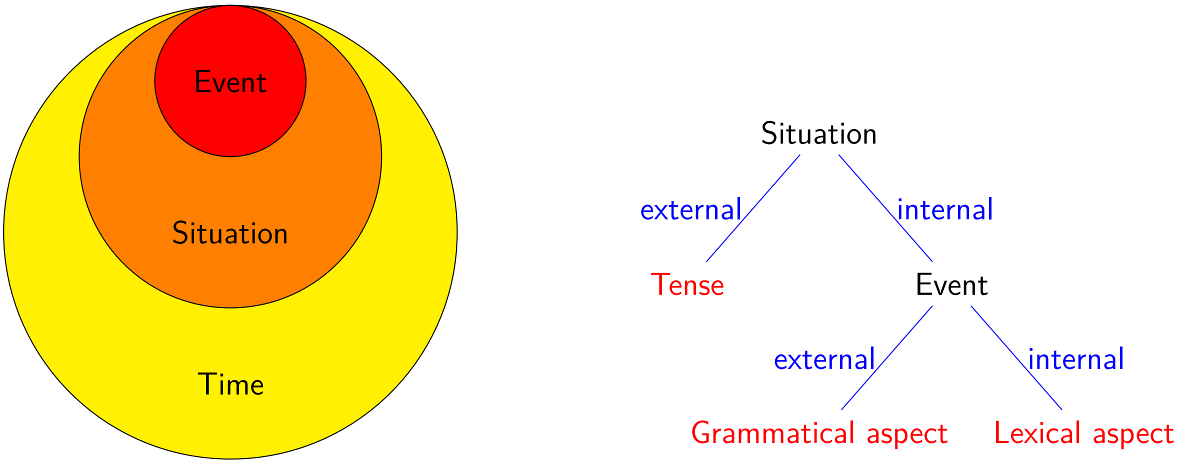


Figure 1: A set-theoretical representation of the relationship between time, situation and event *(left)* along with the categorisation of the three temporal phenomena discussed *(right)*.

2.1.1 Lexical vs grammatical aspect

The polysemy of the term "aspect" in the linguistic community is unfortunate. In an area of language which seems to have surprisingly far-reaching interactions with other parts of linguistic systems these ambiguities are particularly unhelpful.[2] As already mentioned, aspect[3] is a term often used to refer to both lexical and grammatical aspect. Lexical aspect (also referred to as *Aktionsart, situation aspect* or *inner aspect*) is the inherent property of a verb or verb phrase which "characterizes the temporal profile of event descriptions" [van Hout, 2016]. For example, to "crack open an egg" is inherently a short event describing the change of one state (the egg being whole) to another (the egg being cracked). Grammatical aspect (or *viewpoint aspect, outer aspect*), on the other hand, describes the "internal temporal constituency" [Comrie, 1976] XCHANGE THIS!! of an event, such as its habituality or ongoing nature and can be seen more as an external lens imposed on a verbal phrase. In English, one example of this lens is the progressive, which is formed by the verb *be* + gerund, as in the phrase "Sue was running".

Figure 1 shows a taxonomy of tense, and grammatical and lexical aspect. An event is an atomic or

Here each situation is a union of events ($\mathbf{situations} = \mathcal{P}(\mathbf{events})\backslash\emptyset$) and the

[2] Among other things, aspect is also intertwined with case, mood and voice [Franks, 2005, Kiparsky, 2004].

[3] Boogaart uses the term *aspectuality* to remove the aforementioned ambiguity [Boogaart, 2004]. However, I will stick with the term *aspect* due to its prevalence in the literature, further specifying where necessary.

Situations are anchored in time.

The concrete linguistic realisation of these categories is very often unclear or non-existent and exhibits a relatively wide variety of encodings throughout the world's languages [Dahl, 1985]. It therefore proves tricky to uphold this distinction in empirical studies "in the real world". This has led some to question to what extent this distinction makes sense [Sasse, 2002]. Those who question the contrast between these two semantic dimensions, described as unidimensionalists in Sasse [2002], claim that aspectual distinctions in both dimensions can be reduced to a common set of semantic primitives, which can be applied to all levels of analysis, i.e. the boundedness of lexical aspect is the same as the boundedness which marks the distinction between the perfective and imperfective parameters.

I have chosen to introduce this distinction in order to WHAT

WHICH MODEL WOULD I LIKE TO USE IN THE END??

Nevertheless the theoretical differentiation of these two interrelated subdomains is an important one to make, and each describes a variety of concepts which will be useful later.

2.1.2 Lexical aspect

Telicity

A fundamental distinction of lexical aspect is that of telicity (from Ancient Greek *télos* meaning "end"). Telicity describes whether an event has an inherent goal or end-point after which the event can be regarded as completed: for example "go climbing" would be atelic whereas "climb the mountain" is telic (since it involves the agent reaching the summit of a mountain). A classic test for telicity[4] is whether the verb phrase admits a completing adverb such as "in an hour" and does not admit a durative adverb such as "for an hour" [Krifka, 1998].

Dahl misleadingly defines telicity as "involv[ing] the presence of a boundary or the attainment of a specific result-state" [Östen Dahl, 2015], which, however can lead to confusion with the term *(un)boundedness*.

[4] Though Xiao and Mcenery [2006] note that this test is flawed and propose an alternative test scheme.

Boundedness

(Un)boundedness refers to the existance (or lack of) a *temporal* boundary marking the end of an action. Boundedness must be distinguished from telicity[5] in order to avoid the so-called 'Imperfective Paradox' highlighted by Linguistics et al. [2005], here verbalised by Zucchi [2020]:

> How is it possible that a statement of the form *x was F-ing* is true and yet there is no time at which *x was F-ed* is true?

More concretely, it asks the question why (1) entails (2) but (3) doesn't entail (4) in the examples below:

(1) The man was running.

(2) The man ran.

(3) The man was building a house.

(4) The man built a house.

Depraetere [1995] shows that this apparent "paradox" can be resolved by distinguishing between these two concepts of telicity and boundedness,[6] and this further serves to show the dangers of misuse of terminology. Table 2.1.2 visualises the relationship between the reference time (temporal boundaries) and the run-time (the inherent "time schema" of the verb phrase). This allows for a clearer definition of boundedness, namely whether the right-hand side of the run-time boundary lies within the reference time or not (IS THIS TRUE?).

[5] Friedrich et al. [2023] seem to mistakenly conflate the two, stating that "[t]elicity is also sometimes referred to as boundedness (e.g., by Loáiciga and Grisot, 2016)" referring to the 2016 paper Loáiciga and Grisot [2016], which, however, clearly distinguishes between the two notions.

[6] By definition of telicity as whether an even has an inherent end-point, and boundedness as whether it has a temporal boundary (separate from its intended end-point) we can distinguish between whether an event has reached its termination or whether it was ended before reaching this end-point. Therefore while it is the case that the both (1) and (2) are bounded, only (3) and (4) contain telic events, and it seems to be the case that the progressive's focus on temporal boundary nullifies the end-point inherent in the verb phrase "build a house". This serves as an interesting example of the interaction between grammatical and lexical aspect.

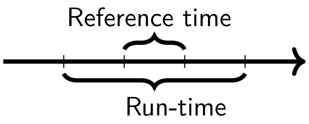
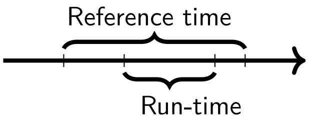
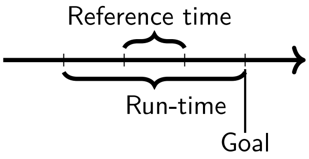
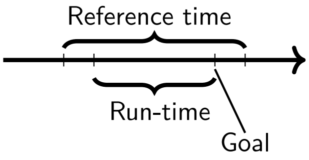
Sentence	Representation	Telicity	Boundedness
The man was running.		atelic	unbounded
The man ran.		atelic	bounded
The man was building a house.		telic	unbounded
The man built a house.		telic	bounded

Table 1: Representation of (1),(2),(3) and (4) with regards to the reference time referred to by the utterance and inherent run-time of the event. Concept adapted from van Hout [2016].

Stativity

Another parameter of lexical aspect I would like to discuss is stativity, which describes a state of being such as "know", "love" or "be", rather than an action [Binnick, 1991]. A classic test for stativity in English is non-admittance of the progressive or the imperative [McIntosh, 1975].[7] Consider the following examples:

(5) She resembles her grandmother.

(6) * She is resembling her grandmother.

Durativity

Durativity denotes whether an event takes time (i.e. has duration) or happens in an instant, and this can be checked in English by the compatibility of durative adverbs such as *for an hour* [Wilhelm, 2007]. For example:

(7) Andrea was painting a picture for an hour.

(8) * Andrea was reaching the summit for an hour.

2.1.2.1 Some attempts at event classification

Vendler [1957]

It was the seminal work *Verbs and Times* [Vendler, 1957] of philosopher Zeno Vender which initiated the discussion on inner aspect in the linguistic tradition.[8] Vendler begins his discussion with the following premise:

[7] Interestingly, however, Granath and Wherrity [2013] find that, assuming a functional-semantic definition if stativity, the usage of stative verbs with the progressive is much higher in spoken language, than in written language.

[8] A similar classification was also developed independently by Anthony Kenny in *Action, Emotion and Will* [Kenny, 1963], however combining Achievement and Accomplishment into one single class [Mourelatos, 1978]. Hence it is sometimes referred to as the Vendler-Kenny scheme of verb-types.

	Static	Durative	Telic
State	+	+	-
Activity	-	+	-
Accomplishment	-	+	+
Achievement	-	-	+

Table 2: Classification of Vendlerian event types by binary aspectual parameters [Smith, 1991].

> Indeed, as I intend to show, if we focus our attention primarily upon the time schemata presupposed by various verbs, we are able to throw light on some of the obscurities which still remain in these matters. [...] There are a few such schemata of very wide application. Once they have been discovered in some typical examples, they may be used as models of comparison in exploring and clarifying the behavious of any verb whatever.[9]

That is to say, the "time schema" of any verb can be described through comparison with a set of prototypical classes (see 2.1.2.1), which can be easily identified. In order to arrive at these prototypical "schemata" he uses an analytical method consisting of classifying verbs according to their behaviour regarding certain elements of English grammar, as was also used to outline the aspectual parameters above.[10] For example, the first distinction he makes is between English verbs that permit the progressive and those that don't. This signals the first class of events known as 'states'. The article then goes on to outline the other three Vendlerian classes *activity, accomplishment* and *achievement*, and their character is summarised thus:

- **State** - non-dynamic, static and durative situation
- **Activity** - open-ended, dynamic and durative processes without an end-point
- **Accomplishment** - dynamic and durative processes with a natural end-point
- **Achievement** - instantaneous or near-instantaneous events (such as semelfactives)

Or to use the parameters of lexical aspect introduced above:

[9] Vendler [1957]

[10] The issue of Anglocentrism is one which has plagued many a linguistic theory throughout the years, with work from Chomsky's generative grammar [Levisen, 2019] to Abstract Meaning Representation [Damonte and Cohen, 2018] being criticised for their too heavy focus on English.

State	**Activity**	**Accomplishment**	**Achievement**
know	running	paint a picture	reach the summit
understand	pushing	build a house	spot the plane
love	smoking	deliver a sermon	recognise

Table 3: Some of the example verb phrases given in Vendler [1957] for the classification of events.

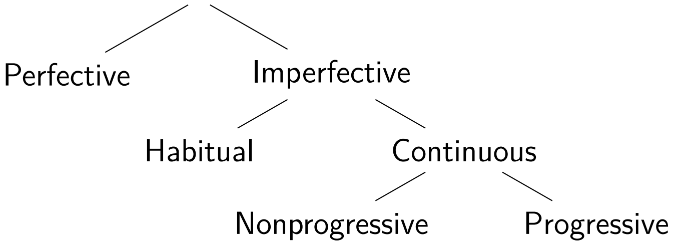


Figure 2: Comrie's classification of aspectual oppositions. Reproduced from Comrie [1976].

Vendler states in his introduction that verbs "presuppose" certain time schemata and hence assigns a category to each verb (as in 2.1.2.1). However it must also be stated that the true profile of a verb phrase such as those listed in 2.1.2.1 depends heavily on the context. Hence a typical semelfactive such as "sneeze" could also be used reinterpreted as a process when combined with a progressive auxiliary as in "Harry was sneezing" [Moens and Steedman, 1988]. Thus the verbs (or verb phrases) mentioned by Vendler as belonging to a certain category are ones that typically lend themselves to one class or another.

Moens and Steedman [1988]

2.1.3 Grammatical aspect

Grammatical (or *viewpoint*) aspect provides a lens through which a particular event is viewed and it "is typically expressed by overt grammatical morphemes (hence the label grammatical aspect)" [Patard et al., 2019]. Comrie [1976] provides a hierarchical classification of aspectual oppositions shown in 2, and in the following section I will briefly describe some of the main oppositions described in this classification: the perfective vs. imperfective opposition and habituality,

Perfectivity

The main aspectual distinction made by Slavic languages and, as can bee seen in figure 2, one of the main distinctions made in theoretical aspectology generally as that between perfective and imperfective. As noted by Dahl [1985], the theoretical distinction between perfectivity and imperfectivity is different to their concrete realisation in the Slavic language group. To avoid confusion, I will therefore henceforth use the terms to 'perfective' and 'imperfective' to refer to the theoretical binary opposition, and only refer to the Slavic (im-)perfectivity explicitly.

Returning to the definition of grammatical aspect as *situation-internal* but *event-external* (REFERENCE), perfectivity can be seen as a focus on the event as a whole indivisible entity (i.e. its result), and imperfectivity implies a focus on its internal temporal constituency [Comrie, 1976, Östen Dahl and Velupillai, 2013]. In practice this often means that perfective verbs refer to "completed" events (EXAMPLE), and imperfective verbs to incomplete or long-lasting events (EXAMPLE), however note that this is not always the case.

Habituality

2.2 Aspectual ambiguity

While some verb phrases can only express one certain aspect, such as *to tend to*, which implies a habitual event, in many situations they can be ambiguous:

(9) Your soul was made to be **filled** with God Himself. *(Brown corpus, cited by Friedrich and Palmer [2014])*

In this example the verb 'filled' can be read as both a stative and a dynamic event.[11] Nevertheless, in many cases the reader tends to prefer a particular interpretation, such as in 10, where the sentence is most likely to be a habitual, a common use of the English simple present, and yet could also be interpreted as a narrative present (RIGHT NAME?) as in 11.

(10) He walks to school.

[11] Indeed, while not specified in English, this is explicitly encoded in other languages such as German where the former interpretation would use the word *sein* (to be) and the latter *werden* (to become).

(11) He walks off to school.

This poses a practical problem for annotators when asked to provide a single class for a sentence (or sometimes even just for a verb phrase as in Siegel and McKeown [2000]), but also an interesting theoretical question for linguists. For simplicity, most studies have assumed that ASPECT IS EINDEUTIG!!. There have been no studies on aspect ambiguity as of yet [Friedrich et al., 2023], despite this being a not too uncommon occurrence in language (see 5.1). Some, such as Van Gysel et al. [2021] (see 4.1.1), have got around this problem by classifying aspect in a lattice structure, allowing for more coarse grained categories when necessary. While perhaps doable in practice, this is in unsatisfactory solution to describe to several semantically distinct interpretations of a particular utterance.

WHAT ARE THE CIRCUMSTANCES IN WHICH AMBIGUITY ARISES IN ENGLISH?

taking out the habitual of course

semelfactives (single / iterative) passive (stativity / dynamicity) -> how is this in Russian? past simple (stativity / dynamicity) Verbs of motion with ambiguous prepositions (telic / atelic)

see - Coercion and underspecification integrated: The state-event ambiguity of aspectual verbs (past simple); Automatic prediction of aspectual class of verbs in context (passive stative / dynamic)

While not directly encoding dynamicity, telicity or iterativity, the choice of perfective / imperfective in Slavic languages is strongly influenced by boundedness and whether an event is a single situation or repeated [Wiemer and Seržant, 2017]. While the latter equates to iterativity, boundedness is also highly correlated with telicity and stativity (?), and hence the (obligatory) choice of PERF/IMPF forces one of the two possible interpretations in each case. Apresyan [2024] also finds that L2 Russian speakers are more likely to choose the incorrect aspect if their L1 does not differentiate between these two interpretations in a particular case, corroborating intuition.

2.2.1 Coercion or underspecification?

10 and 11 are an example of how, when underspecified, a verb phrase in a sentence can tend towards a particular aspectual interpretation, however further specification leads to a different

interpretation. In cases where a verb can have several aspect readings depending on the context, a question that currently remains unclear is whether verbs have an inherent aspect class, which is *overwritten* by the features of the context is occurs in (temporal adverbs, other verb phrases forcing a particular class such as *to tend to* etc.), or whether they are simply underspecified in the mental lexicon, and the class is *determined* by these circumstantial features [Gerwien and Herweg, 2017]. The former view, as put forward by Moens and Steedman [1988] and known as *coercion*, is used as an assumption in many previous works (cf. de Swart [2019]) with little evidence of its validity [Gerwien and Herweg, 2017].

2.3 Aspect in Slavic languages

The Slavic language group has a special place on the study of aspectology due to its overt encoding of aspectual phenomena, otherwise rather uncommon [Tomelleri, 2010].[12] Verbs in Slavic languages, with few exceptions (CHECK IF THIS IS TRUE), are either perfective or imperfective, meaning the speaker must explicitly state the aspect of the verb event referenced.

(12) Ja proCCitaju Etu knigu.

(HOW DO I DO THE GLOSSING HERE)

As mentioned, the opposition between these two lexical categories differs slightly from the "purer" theoretical distinction discussed in 2.1.3. A classic example where the usage does not correspond to the WHAT is the pair 13 and 14, where the former is a prototypical usage of the perfective to denote a whole completed event, the latter imperfective form denotes that the event has since been undone (CHECK THIS) [Franks, 2005].

(13) Kto otkryl okno?

(14) Kto otkryval okno?

It is also interesting to note that modern Slavic aspect, now usually seen as a *grammatical* feature, developed from spatial prefixes ??? The most common perfectivising prefix *po-* used to refer

[12] Tomelleri [2010] also notes that Georgian and Ossetian exhibit some similar properties with preverbs (mostly of spatial origin) used to denote aspectual meaning.

to WHAT, however has slowly developed into a temporal marker and finally into a grammatical aspect marker.

The diachronic (GRADUAL?) grammaticalisation of lexemes exhibited by Slavic languages is further evidence in favour of a less clear distinction between grammatical and lexical aspect. WE CAN SEE THE DIACHRONICAL DEVELOPMENT FROM LEXICAL ASPECT TO GRAMMATICAL ASPECT

It is due to this covert aspect marking that I decided to include Slavic languages in this study, and

2.4 Formal models of aspect (or put this in related work?)

Finally, I would like to outline some of the formal logical approaches that have been made in this area

3 Related Work

3.1 Aspect classification

Aspect has received comparatively very little attention from the computational linguistics community[Friedrich et al., 2023], especially from the Natural Language Processing (NLP) part of the field.[1] However there have been some works in recent years looking at this area.

3.1.1 Rules-based aspect class prediction

Siegel and McKeown [2000] develop a rules-based aspect classification of verbs using co-occurrence information from a corpus. The aspect class they aim to predict is an inherent class of a verb (i.e. lexical aspect) and hence they do not take into account the sentence context, which often has an effect on the aspect of the verb considered. This is one of the issues which makes aforementioned distinction between lexical and grammatical aspect so difficult in practice.[2] The aspect classification scheme they used was that of Moens and Steedman [1988], a 5-way class distinction building on Vendler [1957].

Interestingly they use their results draw the following linguistic conclusions: HERE.

Egg et al. [2019] do something cool too.

TALK ABOUT ASp-Ambig - be we have a different type of ambiguity

Chen et al. [2021] do something.

3.1.2 (L)LMs and aspect

Metheniti et al. [2022] are bros and it WORKS.

[1] As opposed to those with more emphasis on the *linguistics* part of computational linguistics.

[2] See WHERE IS THIS for a more in-depth discusion on coercion and underspecification and their consequences.

3.2 Available datasets

3.3 Formal representations of aspect

3.4 Related areas

3.4.1 Situation entities

Situation entities classification is the task of identifying different types of situations, which exist at a clausal level. The task is comes more from the tradition of discourse analysis, since it is important for discourse representation theory (DRT) to know for example which new referents are introduced to a discourse and or also to analyse temporal relationships. Works usually use the original 8 types introduced by Smith [2003]: events, states, generalizing sentences, generic sentences, facts, propositions, questions and imperatives. While

4 Methods

This is the description of the methods.

- UMR Dataset creation

- Llama Fine-tuning

- Llama for more training data

- Fine-tune smaller (multilingual model)

- Identifying and examining ambiguous sentences/verbs

- Comparing across languages

4.1 Which aspect types do I use?

One inherent drawback of computational methods is exactly their one unifying characteristic: their computability. Sadly, the requirement for computability means, in many cases, sacrificing the nuance that comes with more qualitative approaches. In this concrete case this means settling for a single aspect classification system. A consequence of the glut of literature in the field is a glut of classification systems to go with it, each with their own idiosyncrasies and each having their own advantages and drawbacks. I will attempt to discuss what I see as the main candidates before deciding on one system and explaining this decision - NO - this was done in aspectology already!!!!SEE ABOVE

reason is of course the contribution to the linguistic community: computational approaches to language have SPURRED ON LOTS OF PROGRESS (cf Chomsky!!!).

The framework I decided on was Uniform Meanign Representation (UMR) [Van Gysel et al., 2021].

4.1.1 UMR

UMR [Van Gysel et al., 2021] was introduced in order to expand and further generalise the attempt to design an abstract semantic representation, as was most successfully pioneered by Banarescu et al. [2013] with Abstract Meaning Representation (AMR). In contrast to AMR, UMR aims to be a typologically-informed abstraction away from English structures, making it more suitable for other similar languages, or, in their own words, making it "a practical and cross-linguistically valid meaning representation designed to meet the needs of a wide range of NLP applications" [Van Gysel et al., 2021].

WHY IS UMR IMPORTANT???? Get Apaho English comparison from Bonn et al. [2023]

Aspect in UMR

UMR describes the following 5 corse-grained aspect classes: (descriptions taken from Van Gysel et al. [2021]), also depicted in figure 3:

- **state** - an unspecified type of state
- **habitual** - an event that occurs regularly in the past or present, including generic statements
- **activity** - an event that has not necessarily ended and may be ongoing at Document Creation Time (DCT)
- **endeavour** - a process that ends without reaching completion (i.e., termination)
- **performance** - a process that reaches a completed result state

How these relate to other aspectual classes can be shown in table 4.

Interesting to note is that these classes conflate the distinction made earlier between lexical and grammatical aspect, most clearly in the class "habitual", which is a paradigmatic example of an outer aspect, rather than one inherent in the verb event itself. However, as can be seen in figure 3, while classes which would usually be seen as grammatical aspect are to be found nearer the top of the tree (on the left), the leaves further down the tree are more examples of *Aktionsarten*. That Van Gysel et al. [2021] make no mention of these different types of aspect is not necessarily surprising, given one of the main design goals of UMR being scalability, itself entailing learnability for annotators. As we have seen (HAVE WE?), the theoretical distinction of inner and outer

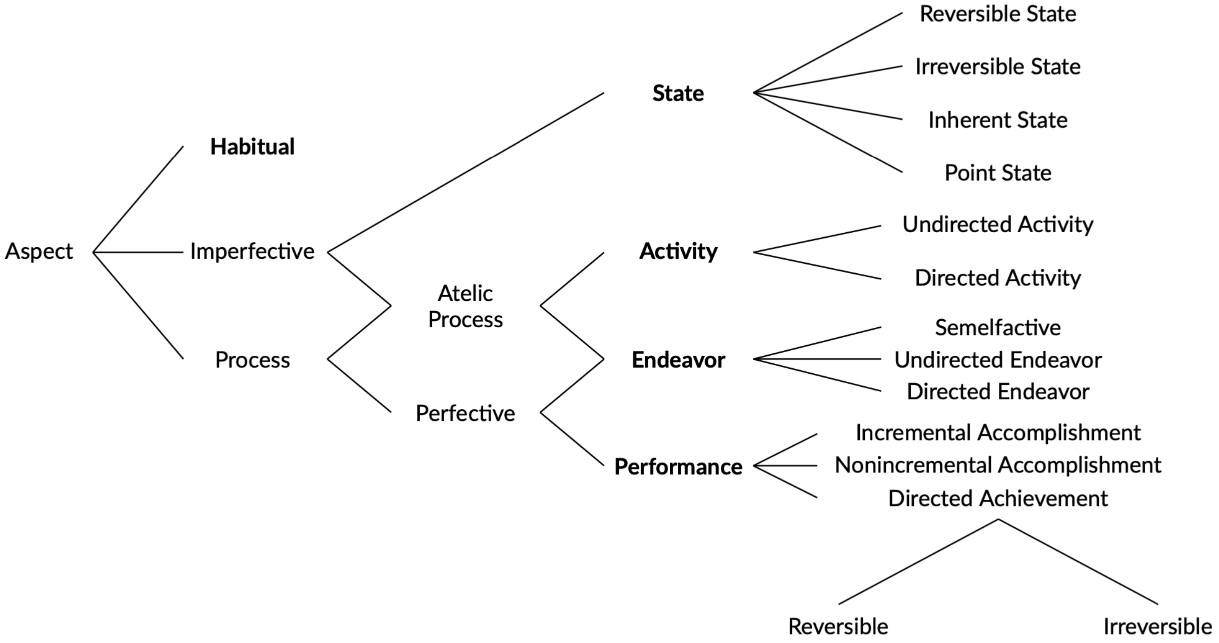


Figure 3: UMR aspect classification tree [Jens Van Gysel and Xue, 2022]

Vendler [1957]	Moens and Steedman [1988]	Egg [2005]	Egg, Prepens, and Roberts [2019]			Van Gysel et al. [2021]
state	state	stative predicate	stative			**state**
	(habitual state)	(CHECK THIS)	-			**habitual**
activity	process	process predicate	dynamic	unbounded		**activity**
accomplishment		intergressive predicate		bounded	extended/no change	**endeavour**
	culminated process	change predicate			extended/change	**performance**
achievement	point	intergressive predicate			punctual/no change	**endeavour**
	culmination	change predicate			punctual/change	**performance**

Table 4: Comparison of aspectual classes. Adapted and extended from Egg, Prepens, and Roberts [2019].

aspect is "very difficult to apply in practice" [Dahl, 1985], hence a clear separation would often be difficult - and indeed not very fruitful - for annotators. This conflation of two phenomena, however, can also be an advantage, since it shows the relationship between classes of each type (i.e. that *irreversible states* are imperfective and *directed achievements* perfective etc.), subsuming them all into *one* semantic parameter space concerning aspect. A further advantage of UMR is the flexibility of annotation levels that can be seen in figure 3. This allows for annotation both at a fine-grained level (using the classes at the bottom of the tree), but also on a more coarse-grained level if instances are unclear or annotators unsure.

Difficulties with aspect in UMR

Slightly different to other frameworks (one category can encompass imperfective and perfective?) - is this true

Habitual as aspect

4.1.2 How does the Slavic Perfective-Imperfective relate to UMR classes

Habitual = imperfective State = imperfective (general imp?) Activity = imperfective (see motion verbs) endeavour =

performance = perfective

4.2 Project outline

4.2.1 Step 1: Use LLM to create dataset

4.2.2 Step 2: Identify aspectually ambiguous sentences

4.2.3 Step 3: Compare aspectual ambiguity cross-lingually

4.3 Use of approximative LMs as sources of linguistic knowledge?? (Reversing the NLP pipeline)

4.4 Where do LLMs fail? (CHANGE - expectation management)

Dataset creation

In order to create the dataset for training the model, later to be used for the neural analysis, it is

Since UMR aspect is an AMR/UMR node parameter, rather than a clausal one (see for example Smith's situation entity types ADD LINK HERE), it is necessary to first parse any sentence into an AMR graph. However, since no parsers are available for Russian, I had to resort to another option. One possibility would be to develop a system, possibly using tools already available for Russian such as syntax parsers ADD EXAMPLE HERE, however since the focus is on one small part of the AMR/UMR graph - nodes describing an event - this could be an unnecessary distraction. In theory at least, AMR graphs should have a strong correlation with the syntax tree representation of the sentence, and since most events are verbal phrases, this fact can be utilised to simpify the problem. I therefore opted to solve the problem by using a dependency parser (OR SYNTAX PARSER???)

5 Dataset Creation

RENAME THIS CHAPTER DATASET CREATION??????

5.1 Dataset creation

In order to carry out further computational analysis of the topic it is helpful to have an annotated dataset. Since no extensive datasets exist beyond for certain aspectual parameters such as telicity [Friedrich and Gateva, 2017] or stativity [Friedrich and Palmer, 2014], I had to create my own [Friedrich et al., 2023]. The traditional route of hand-annotating including has been a standard paradigm for many years however is highly time-intensive. Crowdsourcing is a more time- and cost-effective way of creating data, however has been shown to be of variable quality [Li, 2024], especially when the task requires more expert knowledge. Furthermore there are a range of biases which can affect data quality [Beck, 2023]. The huge success of Large Language Models in recent years has prompted some to look at utilising them for dataset annotation either combined with human annotators [Goel et al., 2023] or on their own [He et al., 2023, Yu et al., 2023, Gilardi et al., 2023], which is what I opted for.

5.1.1 Dataset annotation with LLMs

Large Language Models' use for annotation data has been demonstrated GIVE SOME EXAMPLES.

Törnberg [2024] formulated a set of best practices when using LLMs as text annotators, which I aim to be guided by. The paper provides guidelines for those wishing to use LLMs as text annotators, in the absence of labelled data. This situation differs from the "paradigmatic" one described in the paper by the fact that there already exist annotation guidelines and limited labelled data, hence the iterative systematic coding procedure described in the paper is not necessary. Nevertheless Törnberg [2024] provides a well-needed framework for this relatively new approach.

Choice of LM model

There has been an explosion of LMs in recent years .....

While many previous studies looking at LLM capabilities choose to look at ChatGPT models due to their notoriety in recent years and general good performance. However, as Törnberg [2024] notes, these models come with several issues: it is unknown what the training data for the model is, leading to problems with transparency, and ChatGPT models have been shown to evolve over time, meaning reproducability is hindered. For these reasons, and also in order to host the model locally for better control (rather than using an API), I chose to use a different model. Meta's Llama 2 model seemed to offer a good balance between the apparent current trade-off between performance and scientific good practice, performing comparatively well in previous studies [Yuan et al., 2023] + OTHER EXAMPLES

Due to hardware constraints, I had to use a technique to improve the efficiency of the model training process since the smallest Llama model is 7 billion parameters. In this case I chose to use PEFT (Parameter efficint fine-tuning) (ADD CITATION), which leverages the insight that LM fine-tuning usually only updates parameters at the end of the model. This made it possible to fine-tune the model without resorting to the huge amount of computing power usually necessary for fine-tuning LLMs.

I experimented both with the standard Llama-2-7b and Llama-2-7b-chat [Touvron et al., 2023], however the latter ended up having difficulties responding in a formulaic way and rather added unnecessary or unrelated information, which is to be expected since it has been fine-tuned to fare well in a dialogue environment. This made it often difficult to extract the model's predicted label to use for evaluation.

During the course of this study, Llama 3 was released to the public CITE LLAMA 3, promising to have better reasoning skills and be better at following instructions effectively, so I therefore tried and compared both models in comparable settings.

Training data

As the only currently existing data containing UMR aspect classes, I used the example UMR dataset[1] provided by the creators of UMR. It contains HOW MANY sentences in 6 languages

[1] ENTER LINK FOR WHERE TO FIND IT!!!!!!

Class	No. examples in UMR data	No. examples in upsampling data	**Total**
Performance	124	1	125
State	55	0	55
Activity	36	2	38
Endeavour	17	14	31
Habitual	2	31	33
Total	234	48	282

Table 5: Aspect classes of annotated verbal events in the UMR dataset.

(Arapaho, Chinese, English, Kukama, Navajo and Sanapana) annotated according to the UMR schema. The texts come from WHERE

In order to extract the verbs in the sentences I used Stanford NLP's Stanza POS tagger CITEEE, utilising the alignment given in the training data to find the corresponding node in the UMR graph and its aspect annotation. Table 5.1.1 shows the class distribution of verbal events extracted from the dataset.

Here it is clear that the *habitual* class is underrepresented, corroborating the results of Dahl [1985]'s study concluding that habituals and related aspect classes have a low frequency in actual use, and hence I manually added some datapoints to improve the balance. The added sentences were either found in existing online datasets and simly labelled with a UMR aspect class by hand or they were both manually composed and then labelled.

Törnberg [2024] points out that, since it is unknown exactly which training data was used to train many LMs, one should exercise caution when evaluating their performance on a test set, since the model may have seen the test data before during pre-training. In this case, while it is impossible to rule out that the UMR dataset was used for Llama 2 pretraining, it is highly unlikely that it has seen the data in this form (i.e. as a sentence, a verb from this sentence and a UMR aspect label for this verb), and since the model was pre-trained with a next-token prediction task, it is very improbable that it would have memorised the labels for the data it is being tested on in my experiments. Nevertheless this cannot be ruled out and must be kept in mind when analysing the results.

One interesting feature of the UMR `:aspect` parameter, is that it is used not only with verbs in the source sentence but also with nouns and adjectives (see for example 5.1.1).

Since Russian NLP tools are scarce, it would be difficult to perform event extraction, so, in order to keep the results comparable between both languages, I chose to just to focus on verbal events. In

```
(s1p / publication-91
   :ARG1 (s1l / landslide-01
      :ARG3 (s1a / and
         :op1 (s1d / die-01
            :ARG1 (s1p3 / person :quant 200)
            :aspect state)
         :op2 (s1f / fear-01
            :ARG1 (s1m / miss-01
               :ARG1 (s1p2 / person :quant 1500)
               :aspect state)
            :aspect state)
         :aspect process)
   :place (s1c / country :wiki "Philippines"
      :name (s1n / name :op1 "Philippines"))))
```

Figure 4: UMR graph of *200 dead, 1,500 feared missing in Philippines landslide.*

my analysis the `:aspect` parameter occurred with a verb in the source sentence 74.8% of the time, meaning most of the data from the UMR dataset could be used.

Prompt engineering

Prompt engineering is a new but important field in NLP, and studies have shown the importance of good prompts when dealing with LLMs [Kaddour et al., 2023, Hsieh et al., 2023, Sahoo et al., 2024]. Törnberg [2024] recommends an iterative prompt engineering process of

The model was given the following instruction for each datapoint:

> The annotation distinguishes five base level aspectual values—State, Habitual, Activity, Endeavor, and Performance. The State value corresponds to stative events: no change occurs during the event. It also includes predicate nominals (be a doctor), predicate locations (be in the forest), and thetic (presentational) possession (have a cat). The Habitual value is annotated on events that occur regularly in the past or present. The Activity value indicates an event has not necessarily ended and may be ongoing at Document Creation Time (DCT). Endeavor is used for processes that end without reaching completion (i.e., termination), whereas Performance is used for processes that reach a completed result state.

Prompt type	Llama 2 7B	Llama 3 8B
No definitions	0.198	0.479
Normal	0.748	0.769
Long	0.688	0.740

Table 6: F1 score on test set from fine-tuning Llama 2 7B and 3 8B on different types of prompt

Class	Precision	Recall	F1-Score	Support
Performance	0.90	0.56	0.69	16
State	0.00	0.00	0.00	2
Activity	0.88	0.58	0.70	12
Endeavour	0.50	0.50	0.50	4
Habitual	0.76	1.00	0.86	37
Accuracy			0.77	71
Macro Avg.	0.61	0.53	0.55	71
Weighted Avg.	0.77	0.77	0.75	71

Table 7: Results on test set from fine-tuning Llama 2 on UMR aspect classes without upsampling. (UPDATE FORMATINGG!!!!!)

followed by the following question:

> Which class does "*{verb}*" belong to in this sentence: state, habitual, activity, endeavor, or performance?"

The results show that without an explanation of the classes, the model fails, achieving roughly random accuracy. WHICH EPOCH ARE THESE RESULTS FORMATINGG

Interestingly the results also show that the extended prompt (WHERE TO LINK THIS) also exhibited poorer performance. This could be due to the fact that it contained more redundant information which is

Quantitative analysis of results

The models seemed to learn the aspect classes relatively well and it is clear that in general, manual upsampling improved results across the board, as is to be expected.

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Performance	0.78	0.88	0.82	16
State	1.00	0.75	0.86	8
Activity	1.00	0.56	0.71	9
Endeavour	0.89	0.62	0.73	13
Habitual	0.81	0.97	0.88	39
Accuracy			0.84	85
Macro Avg.	0.90	0.75	0.80	85
Weighted Avg.	0.85	0.84	0.83	85

Table 8: Results on test set from fine-tuning Llama 2 on UMR aspect classes with upsampling. (UPDATE FORMATINGG!!!!!)

5.1.2 (Manual!!) Ambiguity annotation

Since there are no existing datasets for aspectual ambiguity, I decided to annotate the training data I created for the Llama model. This means that I end up with a database of ambiguous sentences which can later be used for testing. This is a relatively hard task for annotation since it is rather open-ended (with $\sum_{i=1}^{5}\binom{5}{i} = 31$ different possible annotations for a verb-sentence pair), and the interpretation of aspect is often rather a subjective process.

The annotation was done by an English native-speaker with a background in philosophy and myself. The annotators were given a detailed description of the UMR classes and asked to assign a class to each sentence-verb pair. If several readings were possible, the annotators were asked to write down all possibilities, indicating an aspectually ambiguous sentence. The annotators were also given the possibility to indicate when they were unsure on a particular sentence. See A.1.2 for the exact annotation guidelines.

For example, the following sentence-verb pair was annotated as belonging to `State` and `Activity` classes and hence has an ambiguous aspectual reading:

(15) The first footage from the devastated village showed a sea of mud covering what had been lush green valley farmland. **covering**

5.1.2.1 (Manual!!) Annotation results

The results of the annotations can be seen in table 5.1.2.1.

	Annotator 1		Annotator 2	
	Absolute freq.	Proportion	Absolute freq.	Proportion
Agreement with UMR[2]	202	0.706	202	0.706
Several labels (ambiguous)	71	0.248	71	0.248
Unsure	28	0.098	28	0.098

Table 9: Analysis of annotated data. GET FOOTNOTE TO WORK HERE!!! AND UPDATE FOR ANNOTATOR 2

It was interesting to note that the majority of occurrences of the habitual class (30 out of 34 or 88% AND WHAT FOR ANNOTATOR 2) were also annotated with other labels, empirically motivating the theory that habituality is located in a different level of aspectual distinction than the other classes. This is also reflected in the UMR aspect lattice (see figure 3), where habituals are on the second highest level of the tree.

Almost all (WHAT NUMBER) the sentence-verb pairs marked with several verb classes by annotator 1 were also marked as ambiguous by annotator 2, however only WHAT PERCENTAGE of those classified as ambiguous by the latter were seen as such by annotator 1. This causes a problem with

(DIFFERENT SETUP NOW)This presents a problem in how to design the experiment set-up. Since we want to encourage the model to learn prototypical examples of aspect classes to make sure it is not overly confident on ambiguous datapoints, it would make sense to remove the datapoints labelled as having more than one class from training set. However, this would lead to the habitual class being almost non-existant in the dataset. One solution would be to leave them in labelled as habituals, but this would lead to WHAT WOULD IT LEAD TO

I therefore chose to keep datapoints which are

5.1.2.2 Consequences for aspectology

Habitual on a different level

5.1.3 Larger dataset

In order to fine-tune the smaller model, a larger dataset is needed than the 209 sentences in the UMR example dataset. The only requirements for this larger dataset are that it is representative, clean and has enough exmaples to train the smaller model. It would also be an advantage if it is a sentence-aligned multilingual corpus, since this would make it possible to test the performance of a multilingual model in other languages where there are no labelled data from the Llama model.

WHY DID WE TAKE OUT HABITUAL? AND NOT ITERATIVE??

6 Experiments

Discussing the results of experiments.

6.1 BERT aspect class recognition

BERT fine-tuning

Due to their size (and the subsequent large amount of data stored in the parameters), it is hard to carry out probing on LLMs, and, due the fact that they appeared recently, there has been less time to develop probing techniques, hence I decided to train a smaller model of the BERT [Devlin et al., 2019] family. These require more data to fine-tune than LLMs, and hence I used the fine-tuned Llama model to generate more training data in a technique known as knowledge distillation (KD). Knowledge distillation involves using a larger 'teacher' model to train a smaller 'student' model, often reaching the same or similar accuracy with a significantly smaller model. While not being able to probe the larger Llama model, smaller models are still an interesting artefact to consider and

Furthermore the complexity of larger LMs (especially those trained for generation rather than sequence classification (CHECK THIS!!!!)) means that their embedding space is noisier than smaller models that have been fine-tuned.

6.2 Ablation (aspectualisation and contextualisation)

6.3 Ablation (aspectualisation and contextualisation)

6.3.1 Probing

6.3.2 Aspect latent space

6.3.2.1 Verb of motion clustering

6.3.2.2 Prefix clustering

Cross-lingual comparison

7 Discussion

Discussing the results.

8 Conclusion

And finally a conclusion.

A Appendix

A.1 Experiments with ChatGPT

Over the last few years, Large Language Models (LLMs) such as GPT-3 [Brown et al., 2020] have achieved great amounts of success over a range of tasks in the NLP domain.

However it has been shown that models such as ChatGPT struggle with mathematical and logical reasoning.

A.1.1 Temporal reasoning

A.1.2 Annotation guidelines

Aspect Annotation Guidelines

This task is about aspect. Aspect is usually grouped as part of a larger linguistic system including tense and mood; however, it is distinct from both. While tense describes where in time an event takes place, aspect is the "lens" through which the event is viewed. For example, the events in both (1) and (2) take place in the past, but they differ through their aspect, meaning different parts of the event are emphasised.

(1) Anna was walking to the park.
(2) Anna walked to the park.

In (1) the continuous aspect is used, meaning the emphasis is on the act of walking to the park, whereas in (2) the emphasis is on the end of the event, i.e. the fact that Anna reached the park. This is why (3) makes sense, but (4) does not.

(3) Anna was walking to the park when she saw Ben. ✅
(4) Anna walked to the park when she saw Ben. ❌

Your task is to classify the verb phrases in the context of the following sentences as one of 5 aspect classes. This annotation distinguishes five base-level aspectual values: State, Habitual, Activity, Endeavor, and Performance.

The **State** value corresponds to stative events: no change occurs during the event. This is also used for modal verbs (*want*, *need* etc.).

I am a doctor. – The glass is shattered. – They have a cat. – He's lying on the bed.[1]

The **Habitual** value is annotated on events that occur usually or often.

I usually wake up at 7. – I go to work by bike.

The **Activity** value indicates a process where it is not clear whether the event has come to an end. This also covers events in the present tense.

He was writing his paper yesterday. – She was phoning someone when I saw her. – He is singing. – They started to laugh. – She kept on playing the violin.

Endeavor is used for processes that end without reaching completion/termination (i.e. an end-point inherent in the process itself).

They mowed the lawn for 30 minutes. – We were walking until dusk.

Performance is used for processes that reach a completed result state.

He denied any wrongdoing. – We reached the summit in 4 hours.

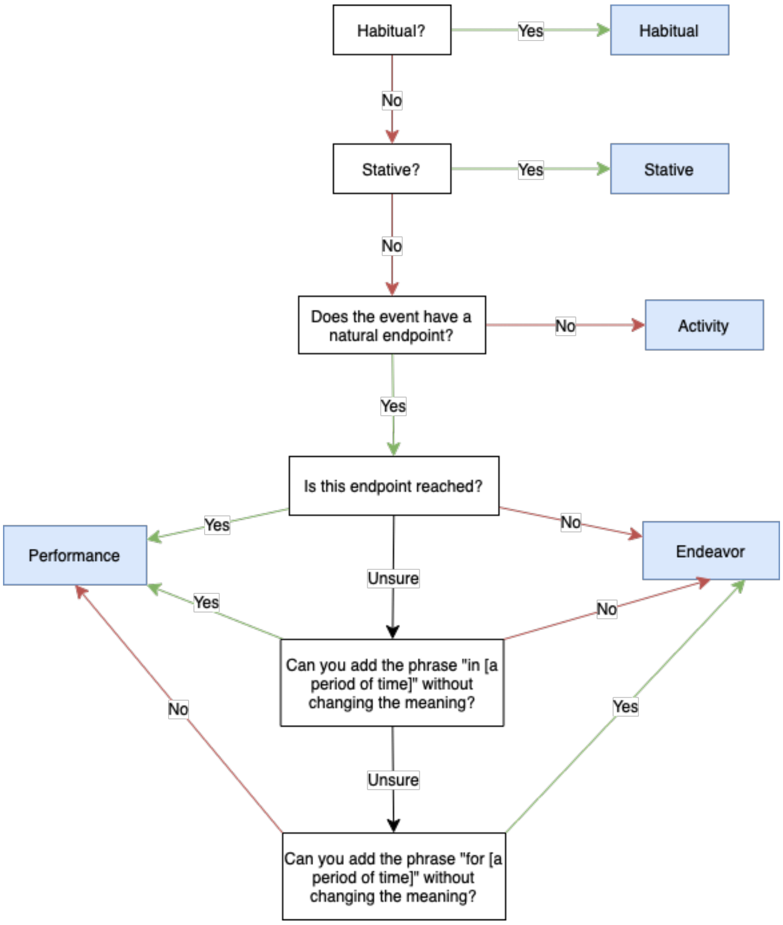
Some sentences have several possible interpretations. For example: "Let the streets be **filled** with song" could be both a state and an endeavor. This is an important part of the annotation. In this case, please enter all classes which are plausible, separated by a comma.

[1] This example is ambiguous and could also refer to an activity since it is a so-called "inactive action".

For convenience, please just enter the *first letter* of the correct class corresponding to the sentence, as in the table shown. See below for an example.

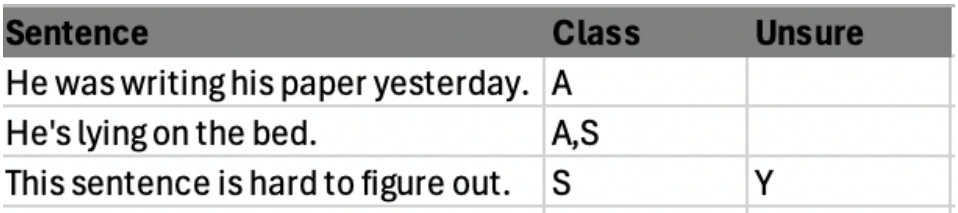
State	S
Habitual	H
Activity	A
Endeavor	E
Performance	P

For further guidance, see the official UMR guidelines or the following flowchart:


Habitual?
Yes
Habitual
No
Stative?
Yes
Stative
No
Does the event have a natural endpoint?
No
Activity
Yes
Is this endpoint reached?
Yes
Performance
No
Endeavor
Unsure
Yes
No
Can you add the phrase "in [a period of time]" without changing the meaning?
No
Yes
Unsure
Can you add the phrase "for [a period of time]" without changing the meaning?

If you are unsure, please enter which of the 5 classes you think fits best, along with a 'Y' in the 'Unsure?' column.

Example:



Sentence	Class	Unsure
He was writing his paper yesterday.	A	
He's lying on the bed.	A,S	
This sentence is hard to figure out.	S	Y

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