CoSimLex: A Resource for Evaluating Graded Word Similarity in Context

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Abstract

State of the art natural language processing tools are built on context-dependent word embeddings, but no direct method for evaluating differences in word sense but more subtle, graded changes in meaning; and covers not only a well-resourced language (English) but a number of less-resourced languages. We define the task and evaluation metrics, outline the dataset collection methodology, and describe the status of the dataset so far.

Keywords: corpus, annotation, semantics, similarity, context, salience, context-dependence

1. Introduction

Recent work in language modelling and word embeddings has led to a sharp increase in use of context-dependent models such as ELMo (Peters et al., 2018) and BERT (Devlin et al., 2019). These models, by providing representations of words which depend on the surrounding context, allow us to take account of the effects not only of discrete differences in word sense but of the more graded effects of context. However, evaluation of these models has generally been in terms of either their performance as language models, or their effect on downstream tasks such as sentiment classification (Peters et al., 2018): there are few resources available which allow evaluation in terms of the properties of the embeddings themselves, or in terms of their ability to model human perceptions of meaning. There are established methods to evaluate word embedding models intrinsically via their ability to reflect human similarity judgements (see e.g. WordSim-353 (Finkelstein et al., 2002) and SimLex-999 (Hill et al., 2015)) or model analogies (Mikolov et al., 2013); however, these have generally ignored context and treated words in isolation. The few that do provide context (e.g. SCWS (Huang et al., 2012) and WiC (Pilehvar and Camacho-Collados, 2019)) focus on word sense and discrete effects, thus missing some of the effects that context has on words in general, and some of the benefits of context-dependent models. To evaluate current models, we need a way to evaluate their ability to reflect similarity judgements in context: how well do they model the effects that context has on word meaning?

In this paper we present our ongoing efforts to define and build a new dataset that tries to fill that gap: CoSimLex. CoSimLex builds on the familiar pairwise, graded similarity task of SimLex-999, but extends it to pairs of words as they occur in context, and specifically provides two different shared contexts for each pair of words. This will provide a dataset suitable for intrinsic evaluation of state-of-the-art contextual word embedding models, by testing their ability to reflect human judgements of word meaning similarity in context, and crucially, the way in which this varies as context is changed. It goes beyond other existing context-based datasets by taking the gradedness of human judgements into account, thus applying not only to polysemous words, or words with distinct senses, but to the phenomenon of context-dependency of word meaning in general. In addition the new dataset is multi-lingual, and includes four less-resourced European languages: Croatian, Estonian, Finnish and Slovene.

The dataset will be used as the gold standard for the final evaluation of a currently running task at SemEval2020: Task 3 Graded Word Similarity in Context.[1]

2. Background

From the outset, our main motivation for the development of this dataset came from an interest in the cognitive and psychological mechanisms by which context affects our perception of the meaning of words. There have been many different ways in the literature to look at this phenomenon,
which lie in the intersection of several different fields of research, and a detailed discussion of the different approaches to this problem is out of the scope of this paper; here, we present two of the most prominent ideas that helped define what we were trying to capture, and made an impact in the design of the dataset and its annotation process. We then look at previous datasets that deal with similarity in context.

### 2.1. Contextual Modulation

Within the field of lexical semantics, Cruse (1986) proposed an interesting compromise between those linguists that saw words as associated with a number of discrete senses and those that thought that the perceived discreteness of lexical senses is just an illusion. He distinguishes two different manners in which sentential context modifies the meaning of a word. First, the context can select for different discrete senses; if that is the case, the word is described as ambiguous, and the process is referred as contextual selection of senses. The second way works within the scope of a single sense, modifying it in an unlimited number of ways by highlighting certain semantic traits and backgrounding others. This process is called contextual modulation of meaning, and the word is said to be general with respect to the traits that are being modulated. This effect is by nature not discrete but continuous and fluid, and since every word is general to some extent: it can be argued that a word has a different meaning in every context in which it appears. Some examples can help to see the different ways in which these phenomena work in real life:

1. We finally reached the bank.
2. At this point, the bank was covered with brambles.
3. Sue is visiting her pregnant cousin.
4. Arthur poured the butter into a dish.

In the first sentence the context doesn’t really help us to select a sense for the word bank. This creates some tension: because bank is such an ambiguous word, we need to select a sense in order for the sentence to properly work. This is an example of ambiguity as opposed to generality. In the second sentence one of the senses is clearly more normal than the other. Cruse (1986) sees the evaluation of contextual normality as the main mechanism for sense selection. In the third sentence, the word cousin could in principle refer to a male or a female. The context is clearly telling us that we are talking about a female cousin, however in this case cousin is a general word that includes male, female, but as well tall, short, happy and sad cousins. The meaning of cousin is being modulated by the context to promote the “female” trait; but notice that the sentence “Sue is visiting her cousin” doesn’t create any tension: cousin is not ambiguous in the true sense. The last sentence is another example of contextual modulation highlighting the “liquid” trait for butter. It is interesting to notice that in this case not only “liquid” is highlighted, related traits like “warm” can be highlighted as a consequence.

These two processes happen very commonly together, with the same context forcing a sense and then modulating its expression. Many different explanations have been proposed for the emergence of these discrete senses, and some may have their origins in very commonly modulated meaning but, according to Cruse, once a discrete sense is established it become some different to contextual modulation and follows different rules:

5. John prefers bitches to dogs.
6. ? John prefers bitches to canines.
7. ? Mary likes mares better than horses.

Here the first sentence works because one of the discrete senses associated to the word dog refers only to male dogs. This cannot be explained by contextual modulation. If that was the case the second sentence, which replaces dog with canine, would work and canine would be modulated in the same way than dog was. The fact that neither canine nor horse can be modulated in this same way indicates that meaning modulation and sense selection are two, strongly interconnected, but distinctive mechanisms of contextual variability.

Given this, it seems clear that the contextual selection of senses would modify human judgements of similarity. For example, the word bank, when used in a context which selects its financial institution sense, should be scored as more similar to other kinds of financial institution (e.g. building society) than when in a context which selects the geographical sense of the word. However, we should also expect that a word like butter, when contextually modulated to highlight its “liquid”, “hot” and “frying” traits, should score more similar to vegetable oil than when contextually modulated to highlight its “animal sourced”, “dairy”, and “creamy” traits. This kind of hypothesis would be testable given a new context-dependent similarity dataset.

Interestingly, Cruse doesn’t find the contrast between polysemy and homonymy particularly helpful, and dislikes the use of these terms because they promote the idea that the primary semantic unit is some common lexeme and each of the different senses are just variants of it. He instead believes the primary semantic unit should be the lexical units, a union of a single sense and a lexical form, and finds it more useful to look at the contrast between discrete and continuous semantic variability. It is true that homonymous words will always fall into the discrete category, but most common understandings of polysemy would include both discrete and continuous variations.

### 2.2. Salience Manipulation

Until now we have looked at contextual variability as an exclusively linguistic phenomenon, a point of view rooted in lexical semantics. We looked at how the context of the sentence affects the meaning of the word. In contrast, cognitive linguistics, and the more specific cognitive semantics, look at language and meaning as an expression of human cognition more generally (Evans and Green, 2018). This approach champions concepts, more specifically conceptual structures, as the true recipient of meaning, replacing words or lexical units. These linguistic units no longer
refer to objects in an external world but to concepts in the mind of the speaker. Words get their meaning only by association with conceptual structures in our minds. The process by which we construct meaning is called conceptualisation, an embodied phenomenon based in social interaction and sensory experience.

Cognitive linguists gravitate to themes that focus on the flexibility and the ability of the interaction between language and conceptual structures to model continuous phenomena, like prototyping effects, categories, metaphor theory and new ways to look at polysemy. Within the cognitive tradition, the idea of conceptual spaces, characterised by conceptual dimensions, has been especially influential (Gärdenfors, 2000; Gärdenfors, 2014). These dimensions can range from concrete ones like weight, temperature and brightness, to very abstract ones like awkwardness or goodness. Once a domain, or selection of dimensions is established, a concept is defined as a region (usually a convex one) of the conceptual space. An example would be to define the colour red as a region of a space made of the dimensions Red, Green and Blue. This geometric approach lends itself perfectly to model phenomena like prototyping (central point of the region), similarity (distance), metaphor (projection between different dimensions) and, more importantly for our concerns here, fluid changes in meaning due to the effects of context.

Warglien and Gärdenfors (2015) use conceptual spaces to look at meaning negotiation in conversation. They investigate the mechanisms, consciously or unconsciously, employed by the people involved in conversation to negotiate meaning of vague predicates, in order to satisfy the coordination needed for communication. These tools help them to decide areas in which they don’t agree as well. All these processes work by manipulating the conceptual dimensions in which meaning is represented. We will refer to them as salience manipulation because their main role is to dynamically rise or lower the perceived importance of certain conceptual dimensions.

The main mechanism by which speakers can modify salience of conceptual dimensions are the automatic priming effects described by, for example, Pickering and Garrod (2004). Mentioning specific words early in the conversation can make the dimensions associated with such words more relevant. Speakers can also explicitly try to remove dimensions from the domain in order to promote agreement, or bring in new dimensions by using metaphoric projections. Because metaphors can be understood as mappings that transfer structure from one domain to another, they can introduce new dimensions and meaning to the conversation.

The lion Ulysses emphasizes Ulysses’ courage but hides his condition of a castaway in Ogiya. Thus metaphors act by orienting communication and selecting dimensions that may be more or less favorable to the speaker. By suggesting that a storm hit the financial markets, a bank manager can move the conversation away from dimensions pertaining to his own responsibilities and instead focus on dimensions over which he has no control. (Warglien and Gärdenfors, 2015)

From this perspective, then, the change in meaning is no longer a change in the meaning of a specific word, but a change in the mind of the hearer (or reader), a change in their mental state triggered by their interaction with the context. In addition, the expectation that priming is the main mechanism for modifying salience has its own implications. Branigan et al. (2000) found that priming effects are much stronger in the context of as natural dialog as possible, when speakers had no time constraints and could respond at their own pace.

This has implications for the design of our dataset and annotation methodology: it is crucial for us to create an annotation process in which the annotator interacts with the context, and does so in as natural a way as possible, before they rate the similarity. Because priming is an automatic process, them knowing that they should be annotating similarity in context becomes a lot less important.

One last interesting consequence of looking at this type of contextual effect is that because the change is in the mind of the annotator, the words that we are rating don’t need to be part of the context. From the classical lexical semantics perspective, meaning change comes from the interaction between the word and the rest of the context; but the cognitive approach suggests that if the context triggers changes in the salience of conceptual dimensions related to particular words being annotated, we should see change in the salience even if those words are not explicitly present in the context. Our goal in this dataset is therefore to create an annotation process that allows us to capture both of these possible contextual phenomena.

### 2.3. Existing Datasets

There are a few examples of datasets which take context into account. However, so far these have been motivated by discrete sense disambiguation, and therefore take a view of word meaning as discrete (taking one of a finite set of senses) rather than continuous; they are therefore not suited for the more graded effects we are interested to look into. The Stanford Contextual Word Similarity (SCWS) dataset (Huang et al., 2012) does contain graded similarity judgements of pairs of words in the context of organically occurring sentences (from Wikipedia). However it was designed to evaluate a discrete multi-prototype model, so the focus was on the contexts selecting for one of the word senses. This resulted in them presenting each of the two words of the pair in their own distinct context. From our point of view this approach has some drawbacks: First, even in the cases where they annotated the same pair twice, we find ourselves with four different contexts, each affecting the meaning of each of the instances of the words independently, and it is not possible to produce a systematic comparison of contextual effects on pairwise similarity. Second, beyond the independent lexical semantics of each word being affected by their independent local context, the annotator is being presented with two completely independently occurring contexts at the same time. Even if the two context did organically occur on their own, this combination of the two didn’t, and we have seen before how crucial
Disease also kills off a lot of the gazelle population. There are many people and domesticated animals that come onto their land. If they pick up a disease from one of these domesticated species they may not be able to fight it off and die. Also, a big reason for the decline of this gazelle population is habitat destruction.

In addition to these limitations of the independent contexts approach, the scores found in SCWS show a worryingly low inter-rater agreement (IRA), measured as the Spearman correlation between different annotators. As pointed out by Pilehvar and Camacho-Collados (2019), the mean IRA between each annotator and the average of the rest, which is considered a human-level upper bound for model’s performance, is 0.52; while the performance of a simple context-independent model like word2vec (Mikolov et al., 2013) is 0.65. Examining the scores more in detail, we find that many scores show a very large standard deviation, with annotators rating the same pair very differently. One possible reason for this may lie in the annotation design: the task itself does not directly enforce engagement with the context, and the words were presented to annotators highlighted in boldface, making it easy to pick them out from the context without reading it; thus potentially leading to a lack of engagement of the annotators with the context.

A lot of these limitations were addressed by the more recent Words-in-Context (WiC) dataset (Pilehvar and Camacho-Collados, 2019). With a more direct and straightforward take on word sense disambiguation, each entry of the dataset is made of two lexicographer examples of the same word. The entry is completed with a positive value (T) if the word sense in the two examples/context is the same, or with a negative value (F) if the contexts point to different word senses. One advantage of this design is that it forces engagement with the context; another is that it creates a task in which context-independent models like word2vec “would perform no better than a random baseline”. Human annotators are shown to produce healthy inter-rater agreement scores for this dataset. However the dataset is again focused with less resources, and as a result the selection of pairs is difficult task: to find suitable, organically occurring contexts is no better than a random baseline”. Human annotators. Finally we calculate the uncentered Pearson correlation. A key property of this method is that similarity between different words. These datasets are also available only in English, and do not allow models to be evaluated across different languages.

3. Dataset and Task Design

CoSimLex will be based on pairs of words from SimLex-999 (Hill et al., 2013); the reliability and common use of this dataset makes it a good starting point and allows comparison of judgements and model outputs to the context-independent case. For Croatian, Estonian and Finnish we are using existent translations of Simlex-999 (Mrkšić et al., 2017; Venekoski and Vankka, 2017; Kittas, 2019). In the case of Slovene, we have produced our own new translation, following the methodology used by Mrkšić et al. (2017) for Croatian.

The English dataset consists of 333 pairs; the Croatian, Estonian, Finnish and Slovene datasets of 111 pairs each. Each pair is rated within two different contexts, giving a total of 1554 scores of contextual similarity. This poses a difficult task: to find suitable, organically occurring contexts for each pair; this task is more pronounced for languages with less resources, and as a result the selection of pairs is different for each language.

Each line of CoSimLex will be made of a pair of words selected from Simlex-999; two different contexts extracted from Wikipedia in which these two words appear; two scores of similarity, each one related to one of the contexts; and two scores of standard deviation. Please see Figure[1] for an example from our English pilot.

Evaluation Tasks and Metrics The first practical use of CoSimLex will be as a gold standard for the public SemEval 2020 task 3: Graded Word Similarity in Context. The goal of this task is to evaluate how well modern context-dependent embeddings can predict the effect of context in human perception of similarity. In order to do so we define two subtasks and two metrics:

Subtask 1 - Predicting Changes: In subtask 1, participants must predict the change in similarity ratings between the two contexts. In order to evaluate if we calculate the difference between the scores produced by the model when the pair is rated within each one of the two contexts. We do the same with the average of the scores produced by the human annotators. Finally we calculate the uncentered Pearson correlation. A key property of this method is that
any context-independent model will predict no change and
get strongly penalised in this task.

Subtask 2 - Predicting Ratings: In subtask 2, participants must predict the absolute similarity rating for each pair in each context. This will be evaluated using Spearman correlation with gold-standard judgements, following the standard evaluation methodology for similarity datasets [Hill et al., 2015, Huang et al., 2012]. Good context-independent models could theoretically give competitive results in this task, however we still expect context-dependent models to have a considerable advantage.

4. Annotation Methodology
As starting point for our annotation methodology, we adapted the annotation instructions used for SimLex-999. This way we benefit from its tested method of explaining how to focus on similarity rather than relatedness or association [Hill et al., 2015]. For English we adopted a modified version of their crowd-sourcing process: we use Amazon Mechanical Turk, with the same post-processing and cleaning of the data (a necessary step when working with this kind of crowd-sourcing platform), and achieve similarly good inter-annotator agreement. For the less-resourced languages, crowdsourcing is not a viable option due to lack of available speakers, and we recruit annotators directly. This means fewer annotators (for Croatian and Slovene, 12 annotators vs 27 in English), however the average quality of annotation is a lot higher and the data requires less post-processing - see Section 5 for details.

4.1. Finding Suitable Contexts
For each word pair we need to find two suitable contexts. These contexts are extracted from each language’s Wikipedia. They are made of three consecutive sentences and they need to contain the pair of words, appearing only once each. English is by far the easiest language to work with, not only because of the amount and quality of the text contained in the English version of Wikipedia but because the other four languages are highly inflected (Croatian, Estonian, Finnish and Slovene). In order to overcome this we work with data from [Ginter et al., 2017] which contains tokenised and lemmatised versions of Wikipedia for 45 languages.

We first find all the possible candidate contexts for each word pair, and then select those candidates that are most likely to produce different ratings of similarity. The differences are expected to be small, especially in words that don’t present several senses and are not highly polysemous, so we need a process that has the most chances of finding contexts that make a difference. We use a dual process in which we use ELMo and BERT to rate the similarity between the target pair within each of the candidate contexts. Then we select the 2 contexts in which ELMo scored the pair as the most similar, and the 2 contexts in which it scored them as most different. We do the same using BERT scores. This gives us 4 contexts in which our target words are scored as very similar by the models and 4 contexts in which they are scored as very different.

The final selection of two contexts is made by expert human annotators, one per language. We construct online surveys with these 8 contexts and ask them to select the two in which they think the word pair is the most and the least similar, trying to maximise the potential contrast in similarity. In addition, we ask them how much potential for a difference they see in the contexts selected. This gives us not only the contexts we need, but a predicted performance and direction of change for use in later analysis.

In the case of less resourced languages, the smaller size and lower quality of the Wikipedia text resources require some extra steps to ensure the quality of the final annotation. For these languages we run the contexts through a set of heuristic filters to try to remove badly constructed ones. In addition we produce 16 candidates instead of 8 for the expert annotators to choose from, and we add the possibility for them to delete parts of the context in order to make them easier to read. Adding text is not allowed, in order to ensure that contexts are natural.

4.2. Contextual Similarity Annotation
The next step is to obtain the contextualised similarity annotations. Our goal is to capture the kind of contextual phenomena discussed in Section 2: lexical meaning modulation and conceptual salience manipulation. In order to maximise our chances we define three goals:

- We want the interaction with the context to be as natural as possible, so as to maximise priming effects and capture the potential change in the salience of conceptual dimensions.
- We need a way in which annotators have the chance to account for lexical modulation within the sentence.
- We need to avoid the apparent lack of engagement we saw in the SCWS annotators.

With these goals in mind we designed a two-step mixed annotation process. Our online survey interface is composed of two pages per pair of words and context (each annotator scores only one of the contexts). In the first page the annotators are presented with the context, and asked to read it and come up with two words “inspired by it”. Once this is complete, the second page shown presents the context again, but with the pair of words now highlighted in bold; they are now asked to rate the similarity of the pair of words within the sentence.

The second page is the main scoring task; it is designed to capture changes in scores of similarity due both to lexical modulation and — because we hope the annotators are still primed by their recent previous engagement with the context — the changes in the salience of conceptual dimensions. The separate task on the first page is intended to make annotators engage fully with the whole context, while maintaining a natural interaction with it to maximise any priming effects. One of the possible problems we identified in the the SCWS annotation process is the fact that the words were always highlighted in bold, making it easy for annotators (Amazon Mechanical Turk workers) to just look at the pair of words in isolation and to not read the rest.

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2 http://hdl.handle.net/11234/1-1989
Word1: ˇcovjek (adult male)  Word2: dijete (child)

| Context1                             | Context1: $\mu = 2.5 \sigma = 1.76$ |
|--------------------------------------|--------------------------------------|
| Špinat ima dosta ˇzeljeza, ali i oksalne kiseline. Oksalna kiselina ve ˇze kalij i ˇchini ga neupotrebljivim za ljudski organizam. Prema novijim istra ˇzivanjima, ˇspinat se ne preporuˇca kao ˇcesta hrana mladim osobama i dijeci, ali je izvrsna hrana za starije ljudje. (Spinach has plenty of iron but also oxalic acid. Oxalic acid binds calcium and renders it unusable for the human body. According to recent research, spinach is not recommended as a common food for young people and children, but it is an excellent food for older people.) |

| Context2                             | Context2: $\mu = 4.25 \sigma = 0.95$ |
|--------------------------------------|--------------------------------------|
| Nakon ˇto su ljudi u selu saznali da je trudna, poˇcinju sumnjati na dr. Richardsona jer je on proveo najviˇse vremena s njom. Kako vrijeme prolazi, pritisak glasina na kraju prisiljava lijeˇcnika da se preseli. Odluˇci se oˇzeniti s Belindom i uzeti dijete sa sobom. (After people in the village find out she is pregnant, they begin to suspect Dr. Richardson because he spent the most time with her. As time goes on, the pressure of the rumors eventually forces the doctor to move. She decides to marry Belinda and take her child with her.) |

Figure 2: Example from the Croatian pilot (translated to English using Google Translate), showing the word pair with two contexts, mean and standard deviation of human similarity judgements. This example showed one of the most significant contextual effects in the pilot; it went in the opposite direction to the one predicted by the expert annotator. Note the effect of stemming: the target word ˇcovjek appears in both cases via its irregular plural, ljudi (nominative) or ljude (accusative); and dijete appears in Context 1 in its dative plural form djeci.

of the contexts. Our initial task is designed to prevent this (the words are not bold in the first page).

In English, given the resources available, we follow SimLex-999 closely: we will use Amazon Mechanical Turk to get 27 annotators per pair and context. Annotators do not score the same pair twice: 27 annotators score the pair within one context and another 27 in the other. This means the whole dataset can be annotated at the same time. Reliability of annotations will be ensured by an adapted version of SimLex-999’s post-processing, which includes rating calibration and the filtering of annotators with very low correlation to the average rating. In addition, we will use responses to the first annotation question to check annotator engagement with the context text and thus filter low quality raters.

For Croatian, Estonian, Finnish and Slovene we recruit annotators directly: this means we have less of them (12 vs 27) but we expect the quality of the annotation to be better (and pilots confirm this – see below). It also means, however, that we must use the same annotators to rate the two contexts of each pair. This has an advantage, because it controls for the variation in the particular judgement of different annotators, but means that we introduce a week’s delay in between annotations in order to make sure they don’t remember, and are influenced by, their own previous score.

5. Current Status

Methodology prototyping We have run three pilots with 13 pairs of words each to confirm the annotation design and methodology. Each study tested a slight variation: in the first pilot, annotators rated relatedness in addition to similarity; the second focused on similarity, and tested the use of contexts related to the target words but not containing them; the third experimented with marking the target words in the context paragraphs using boldface font.

The first pilot confirmed that (as with SimLex) similarity is a more useful metric for this task than relatedness, displaying a higher inter-annotator agreement and more variation between contexts; we therefore use similarity as the basis of our dataset, as described above.

The results of the second pilot saw significant contextual effects in many examples, including some in which the target words weren’t included in the contexts. This indicates that our method seems suitable for capturing priming effects and salience manipulation, or at least some kind of cognitive effects different from lexical contextualisation.

The third pilot showed much lower agreement and lower difference between contexts: we take this as confirmation of our suspicion (from analysis of SCWS) that marking the target words makes it easy for annotators to ignore the rest of the context paragraph, and therefore use the two-stage annotation methodology described above, in which target words are not initially marked.

Results The results from tests so far are very promising in terms of both the difference in judgements between contexts, and inter-annotator agreement. In the English pilot with the closest design to the current one (the second pilot described above), we collected 27 different ratings for each pair and each context: see Table II for detailed results. In addition to the English pilots we have run two pilots in Croatian and Slovene. Please see Table II and Figure 2 for the general results of the Croatian pilot and one of the best examples that came from it respectively.

Inter-rater agreement (IRA) was measured as Spearman correlation between each rating and the average: for the English, pilot, the mean was $\rho = 0.79$, with average standard deviation $\sigma = 1.6$; these compare well to other related datasets (SimLex-999 $\rho = 0.78$, SCWS $\rho = 0.52$). IRA was very high for the Slovene pilot $\rho = 0.82$; significantly lower but still reasonable for the Croatian one $\rho = 0.68$.

In the English pilot, about a third of the pairs show a significant difference in the ratings between contexts, as assessed by a Mann-Whitney U test at $p < 0.05$. The Slovene and Croatian pilots are very small (6 annotators per pair/context) and it is currently difficult to know how sig-
significant their results are (but see Table 2 for indications as to the most likely differences); they have however provided invaluable feedback on methods required for the particularities of these highly inflected, less-resourced languages.

At the moment of writing this paper we are preparing to run a second round of pilots in Croatian and Slovene to test the design presented in the previous section. In the pilots so far, annotators were not asked explicitly to rate the words “within the contexts”; while this should have encouraged pure priming effects, minimizing lexical modulation effects, and the fact that we obtained significant differences is encouraging, we expect that larger and more reliable differences will be obtained if annotators are explicitly told to consider the contexts. Our new pilots therefore use a more explicit question about similarity “in the context of the sentence” in order to promote strong lexical effects.

6. Conclusion

The growing use of context-dependent language models and representations in NLP motivates the need for a dataset against which they can be evaluated, and which can test their ability to reflect human perceptions of context-dependent meaning. CoSimLex will provide such a dataset, and do so across a number of less-resourced languages as well as English. The full dataset will be available for the evaluation stage of SemEval2020 at the beginning of February 2020, and be made public when the competition is over (before the LREC2020 conference).

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| Word1 | Word2 | SimLex | Context1 | Context2 | STDev\_SL | STDev\_C1 | STDev\_C2 |
|-------|-------|--------|----------|----------|------------|------------|------------|
| captain | sailor | 5.00   | 5.20     | 6.44     | 1.43       | 1.93       | 1.77       |
| corporation | business | 9.02 | 9.24     | 9.51     | 1.44       | 0.78       | 0.69       |
| god | spirit | 7.30 | 5.65     | 5.30     | 1.63       | 2.47       | 1.90       |
| guilty | ashamed | 6.38 | 7.78     | 6.14     | 0.47       | 1.88       | 1.73       |
| lawyer | banker | 1.88 | 1.62     | 2.54     | 1.18       | 1.51       | 2.01       |
| leader | manager | 7.27 | 8.08 | 7.65 | 1.43 | 1.19 | 1.34 |
| population | people | 7.68 | 6.49 | 7.73 | 0.80 | 2.37 | 1.92 |
| rabbi | minister | 7.62 | 7.85 | 8.11 | 1.35 | 2.29 | 1.21 |
| sheep | cattle | 4.77 | 4.37 | 4.47 | 0.47 | 2.36 | 2.04 |
| task | woman | 0.68 | 0.15 | 0.15 | 0.34 | 0.42 | 0.40 |
| wealth | prestige | 6.07 | 5.20 | 6.67 | 1.55 | 2.05 | 1.74 |

Table 1: Results from the second English pilot including mean ratings and standard deviation for each context, and the original SimLex values for comparison. Rows shown shaded show a significant difference between ratings for Context 1 and Context 2 (Mann-Whitney U test \( p < 0.05 \)).

| Word1 | Word2 | Predicted Potential | Context1 | Context2 | STDev\_C1 | STDev\_C2 |
|-------|-------|---------------------|----------|----------|------------|------------|
| bog | duh | Noticeable difference | 3.75 | 2.50 | 0.96 | 2.17 |
| čovjek | dijete | Small difference | 2.50 | 4.25 | 1.76 | 0.96 |
| ideja | slika | Noticeable difference | 3.33 | 2.00 | 2.16 | 0.82 |
| nedavan | nov | Big difference | 4.17 | 3.25 | 1.47 | 2.22 |
| područje | regija | Small difference | 5.50 | 5.33 | 0.58 | 0.82 |
| presudan | važan | Small difference | 5.33 | 5.00 | 0.82 | 0.82 |
| rijeka | dolina | Noticeable difference | 0.33 | 0.75 | 0.82 | 0.50 |
| škola | pravo | Noticeable difference | 1.75 | 0.50 | 2.22 | 0.84 |
| sunce | nebo | Small difference | 1.50 | 2.50 | 1.87 | 1.73 |
| uništiti | izgraditi | Small difference | 0.25 | 0.83 | 0.50 | 1.60 |
| velik | težak | Noticeable difference | 3.75 | 1.67 | 1.71 | 2.66 |
| znati | vjerovati | Small difference | 2.25 | 2.17 | 1.71 | 1.72 |

Table 2: Results from the Croatian pilot. In addition to the mean score values it shows the Predicted Potential for contextual differences, as judged by the single expert annotator. In each case, Context 1 was the context in which the expert annotator expected the words to be perceived as more similar, and Context 2 as less similar (this applies only to order of presentation here, not to the annotators). Rows shown shaded suggest a trend towards significant difference between ratings for Context 1 and Context 2 (Mann-Whitney U test \( p < 0.15 \)).