How to marry a star: Probabilistic constraints for meaning in context

Katrin Erk  
University of Texas at Austin, katrin.erk@utexas.edu

Aurelie Herbelot  
University of Trento, aurelie.herbelot@unitn.it

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Most words can take on different meanings based on their context. Some influences come from local context, like selectional preferences, e.g., the agent of a sleeping event is generally an animate being. But global context also plays a role. (1) is a contrast pair with different senses of the word ball (sports equipment vs. dancing event). Arguably, the sense of the predicate run is the same in (1-a) and (1-b), so the difference in the senses of ball must come from something other than direct semantic neighbors. We can characterize this influence as global topical context brought about by the presence of athlete in the first sentence, and violinist in the second.

(1) a. The athlete ran to the ball.
   b. The violinist ran to the ball.

There is even a whole genre of jokes relying on a competition of local and global topical constraints: the pun. In sentence (2), the pun rests on two senses of the word star, which can be paraphrased as ‘well-known person’ and ‘sun’.

(2) The astronomer married the star.

It is interesting that this sentence should even work as a pun: The predicate that applies to star (marry) clearly selects for a person as its theme. So if the influence of local context were to apply strictly before global context, marry should immediately disambiguate star towards the ‘person’ sense as soon as they combine. But the ‘sun’ sense is clearly present.

As Del Pinal (2018) points out, much of the flexibility of word meaning can be explained through conceptual knowledge associated with lexical items, rather than general pragmatic reasoning. We make a similar argument for topical context which, as we saw in (1), can be rooted in the conceptual correlate of lexical items (e.g., athlete invokes sport equipment rather than high-society events).

We model both local and global context as a system of interacting, probabilistic constraints that let the listener imagine the scene described by a given utterance. So we obtain a probabilistic generative model that describes utterance understanding as a process of generating a description of a situation, subject to both local and global constraints associated with the lexical items. This process can be viewed as a formalization of Fillmore’s “semantics of understanding” or ‘U-semantics’ (Fillmore, 1985), the aim of which is to give “an account of the ability of a native speaker to ‘envision’ the ‘world’ of the text under an interpretation of its elements” (p. 235). The idea is that the listener uses the frames that are ‘evoked’ by the words in the utterance to “[construct] an interpretation of the whole” (p. 233), a full description of a scene, including elements that may not be explicit in the original sentence.
Our model encompasses both a conceptual and a referential representation of meaning, where the generative process is such that the conceptual representation generates the conditions of a Discourse Representation Structure (DRS, Kamp and Reyle (1993)). Fig. 1 provides an illustration of the generative process using the sentence “A star shines”. At the bottom of the figure is the DRS; everything above it constitutes the conceptual representation of the utterance. The referents and conditions of the DRS in black represent the original utterance, the material in grey is added as the listener ‘fleshes out’ the utterance, adding e.g. a sky as the Location of the star.

At the conceptual level, each referent in the DRS is associated with a concept (light blue). Selectional constraints (darker blue) and concepts jointly generate finer-grained feature vectors to account for meaning modulation, following e.g. Asher (2011) and McNally and Boleda (2017). The feature vectors then generate the DRS conditions for that referent. Each concept is further associated with a scenario (light green), where formally a scenario is simply a distribution over concepts. The sole global constraint is the distribution over scenarios (scenario mix, yellow). Through a soft constraint that prefers sparse scenario mixes, with only few different scenarios, we immediately obtain representations that tend to be topically coherent.

We formalize the process as a situation description system (SDS). An SDS generates a representation of an utterance not as single situation description, as shown in Fig. 1, but a distribution over situation descriptions. For instance, the star shines might evoke a situation description containing a bright celestial object with 0.9 probability and a situation description with a witty entertainer with 0.1 probability. The evoked concepts provide something akin to traditional ‘sense disambiguation’: generating a concept CELESTIAL OBJECT rather than ACTOR in a given situation description clearly selects a given sense of the word star. However, our own notion of a word’s meaning is more fine-grained and can be expressed as a function of the entire network of concepts, scenarios and attributes that accounts for its presence in the utterance.

The framework also accounts for utterances where senses oscillate between two readings, as in The astronomer married the star, where the associated distribution over situation description would contain descriptions of both prominent readings. Figure 2 sketches one reading of the astronomer sentence, with the competing selectional constraint and scenario outlined in red. This reading would be obtained because of the sparseness preference for scenario mixes. Similarly, in cases where the sentence is ambiguous without being a pun (e.g. I saw the star), the probability distribution over scenarios will generate the relevant readings as separate situation descriptions. We can further imagine scenario probabilities to be influenced by previous discourse, leading to non-uniform priors.

Small-scale examples of the framework have been implemented to illustrate the behaviour of the system with respect to a) global constraints (when does bat evoke a gothic novel rather than a baseball game?); b) local constraints at the semantic role level (when hearing the vampire eats, which food will the listener most likely infer?); and c) modifier-head combination at the local feature level (what are the features of a fanged bat?). We finish our exposition by showing how the SDS can also remain agnostic about sense when presented with a pun.

The next task will be to scale our implementation to account for arbitrary English sentences. We would then like to evaluate the framework on its ability to simulate human behaviour on tasks like meaning similarity prediction and paraphrasing, as well as expectations on upcoming words.

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A Appendix: Example output

We give here two illustrations of the behaviour of
our system when given an utterance, showing how
it implements particular characteristics of natural
language comprehension, and how meaning con-
textualisation naturally derives from such charac-
teristics. The system is implemented in the proba-
bilistic programming language WebPPL (Goodman
and Stuhlmüller, 2014).

To illustrate how a situation description system
fills in the details of an utterance, we inspect the
behaviour of the system when presented with the
utterance A vampire is eating. We have set the verb
eat to probabilistically take a patient with high
probability, and a location with lower probability.
We want to show how a listener fills in the details of
the sentence using their prior world knowledge. We
sample 2000 situation descriptions for the utterance
in a system that has a single scenario containing the
concepts VAMPIRE, EAT, BLOOD ORANGE, BAT-ANIMAL,
and CASTLE. We have set the patient
role of EAT to strongly prefer food stuff (that is, the
concept BLOOD ORANGE has by far the highest
probability), and the location to prefer buildings
over other concrete objects. Despite not being ex-
plicitly realized in the utterance, the patient role
is activated with probability 0.71 and the location
role with probability 0.25. Table 1 shows the prob-
abilities of situations descriptions with particular
patients / locations. As we can see, our vampire’s
food is most likely to be oranges, and she is more
likely to eat in a castle than located at an orange.
Since we are implementing soft constraints, though,
we do also retain small probabilities that she is eat-
ing another vampire, a castle or a bat.

Secondly, we return to the pun example The astron-
omer married the star, which plays on con-
licting constraints (one coming from the scenario
level, one from the selectional preference of the
verb marry). We now illustrate how our system
retrieves both senses of star in different propor-
tions. In particular, we show that we can control
the interpreter’s preference with respect to ‘mixing
scenarios’ through a parameter of the probability
distribution from which we draw a distribution over
scenarios. This is the concentration parameter $\alpha$ of
the Dirichlet distribution. By setting the parameter
to prefer only having few scenarios in the mix, we
introduce a competition of the scenario mix with
the verb’s selectional preference. We set the theme
of MARRY to strongly prefer person fillers but also
allow arbitrary object fillers with lower probability.
Fig 3 shows the percentage of STAR-SUN concepts
returned across 2000 situation descriptions, for dif-
f erent values of $\alpha$. The $\alpha$ of 0.5 clearly prefers the
person sense of STAR. As we decrease $\alpha$ and more
strongly prefer to stay within a single scenario,
however, more and more sun senses are introduced,
resulting in the typical pun effect where the listener
is left hanging between interpretations.

<table>
<thead>
<tr>
<th>Concept</th>
<th>p Patient</th>
<th>p Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>BLOOD-ORANGE</td>
<td>0.64</td>
<td>0.004</td>
</tr>
<tr>
<td>VAMPIRE</td>
<td>0.02</td>
<td>0.005</td>
</tr>
<tr>
<td>BAT-ANIMAL</td>
<td>0.03</td>
<td>0.004</td>
</tr>
<tr>
<td>CASTLE</td>
<td>0.02</td>
<td>0.24</td>
</tr>
</tbody>
</table>

Table 1: Probabilities of situation descriptions with par-
ticular patients / locations for the utterance A vampire
is eating.

Figure 3: Percentage of STAR-SUN concepts for differ-
ent values of the soft constraint that prefers few scenar-
ios (the Dirichlet concentration parameter $\alpha$.)