

Grammar Scaling: Leveraging FrameNet Data to Increase Embodied Construction Grammar Coverage

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Abstract

Construction grammars are commonly written by hand. This is not only time and resource intensive, but also limits the potential for applications that need to extract accurate and deep semantics from real-world language. In the present paper we explore novel ways to tap into existing resources to expand Embodied Construction Grammar (ECG) semi-automatically from FrameNet, an approach motivated by the shared theoretical underpinnings of ECG and FrameNet. We show how FrameNet data can be readily translated into ECG *constructions* and *schemas*, and discuss ways to identify the kinds of general patterns that are crucial to construction grammar approaches. The results achieved thus far indicate how a data-driven approach to construction grammar development is not only desirable but feasible.

Introduction¹

The automatic identification of meaningful, event-related information from text presents both an opportunity and a challenge to construction grammar approaches, especially when paired with frame semantics. On the one hand, since constructions represent form-meaning pairings, they are well-suited for representing the patterns by which meanings are expressed in language. Additionally, frame-based semantic representations provide a natural way to capture meaning about events, event participants, and the relations between participants and events, at various granularities. On the other hand, grammars are built by hand in most construction grammar approaches, thereby limiting their coverage and potential application to wide-scale computational applications.

The grammar formalism of Embodied Construction Grammar (Bergen and Chang 2005, Feldman et al. 2010) has facilitated its computational implementation and successful application in various language understanding applications, including robot control and interaction (Trott et al. 2016) and voice-controlled computer gaming (Oliva et al. 2012). However, the coverage of current ECG

grammars is still quite limited. Expanding coverage by hand is time and resource intensive. Moreover, there are methodological concerns, since a grammar designed entirely by hand runs the risk of reflecting the biases of its human designer, rather than capturing the nuances and variations of actual language use.

The current work is motivated by an effort to find ways to semi-automatically increase the scale and complexity of the language that can be analyzed by an ECG grammar, thus enabling a broader range of applications that require rich and deep semantic analysis. FrameNet (Ruppenhofer et al. 2016), with its 10,000+ lexical units and 1,200+ frames, is an obvious resource to help expand ECG grammar size. Crucially, their common roots in Frame Semantics (Fillmore 1982; Chang et al. 2002; Petruck 1996; Dodge and Petruck 2014) provide the conceptual compatibility necessary to this approach. Importantly, FrameNet (FN) is supported by corpus evidence: FN data is based on and linked to actual language use. FN thus provides a means to take a more data-driven approach to increasing grammar coverage.

As we show, building computational tools to visualize and manipulate the FN data makes it possible to better appreciate and more fully tap this rich resource. Further, we discuss how FN resources can be leveraged to substantially and (semi-) automatically expand both the semantic and constructional coverage of the grammar. Another objective of the current work is to automate this expansion process to the fullest extent possible, in order to make this scaling method more feasible.

In the following sections, we first provide some background on Frame Semantics, FrameNet, and ECG. Then, we discuss ways to expand ECG grammar coverage, first looking at frame-based meaning representations, and then at the ways that FN annotated data can be used to hypothesize and generate ECG constructions.

Frame Semantics and FrameNet (FN)

Frame Semantics analyzes language meaning using frames, which are experience-based schematic conceptualizations of scenes, participants, and their relations to one another. The FN knowledge base (Baker

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et al. 2003) takes frame semantics as its conceptual foundation, and provides information about how individual English word and sentence meanings are linked to, and express, frames and frame elements (e.g. a given scene and its participants). FN consists of two key databases. One consists of lattices of frames, and the lexical units which evoke them. The other is a database of sentences that have been annotated with respect to these lexical units and frames. Both FN frames and annotations can be used to expand ECG grammar coverage, and are described more fully in the sections below.

FN data provides a formal representation of rich semantics. By linking word and sentence meaning to frames, it is possible to identify the event(s), event participants, and relations expressed by a given sentence. For instance, in (1), *throw* is a lexical unit in the **Cause_motion** frame, and annotation indicates that *The boy* is the Agent whose action causes the Theme (*a ball*) to move to a Goal (*the pool*).

- (1) *The boy* _[Agent] **threw** _[Target] *a ball* _[Theme] *into the pool* _[Goal]

FN's frame structure thus makes it possible to situate lexically-specific meaning within a broader conceptual framework, facilitating semantic analyses at different granularities of generalization. It is possible to draw frame-level generalizations about the types of events and event participants being expressed by the different lexical units associated with a given frame. Frame-to-frame relations enable still broader generalization over groups of semantically-related frames.

The semantically rich FrameNet data has been used in other computational applications, most notably in the development of automatic frame-based semantic role (SR) labelling (e.g. Das et al. 2014, Hermann et al. 2014). Unlike these approaches, our objective is to make full use of the rich FN data to identify and represent constructions, which explicitly capture the patterns by which frame-based meanings are expressed. Further, this construction grammar approach provides representations that give linguistic insights into language use.

Embodied Construction Grammar (ECG)

As with other construction grammars, Embodied Construction Grammar (ECG) constructions are form-meaning pairings (Bergen and Chang 2005; Feldman et al. 2010). A given sentence is analyzed as instantiating multiple constructions; the overall form and meaning of the sentence is a composition of these individual constructs. For instance, example (1) instantiates several phrasal constructions, including an Argument Structure (A-S) construction (Goldberg 1995, 2006; Dodge 2010; Croft 2012) that specifies how the verb and its arguments (NP: *a ball*, and PP: *into the pool*) are used to describe a

particular event (Cause_motion) and its participant roles (*Target* and *Theme*).

In ECG, constructional meaning is represented using schemas, conceptual knowledge structures that contain generalized information about different types of events, objects, processes, and relations. Thus, schemas are -- by design -- similar in many respects to FN frames. Crucially, ECG schemas are rooted in perceptual and sensorimotor experiences. This draws on the theory of embodied cognition, the idea that all of human cognition, including high-level reasoning, is facilitated by embodied experiences in the physical world (Feldman 2006).

ECG provides a formalism for representing both constructions and schemas, as described more fully later in this paper. ECG has also been computationally implemented beyond a descriptive formalism. Grammars can be viewed and designed using the ECG Workbench (Gilardi 2009). The ECG Analyzer (Bryant 2008) can be used to parse natural language input using an ECG grammar as a model for language. The output of the analysis is a data structure called a Semantic Specification (SemSpec), a meaning representation in the form of schemas, roles, bindings, and role-filler information. In this way, the SemSpec serves to specify which kind of event(s) a given sentence describes, as well as indicating the fillers of event roles. When there is more than one event, it specifies how the events are related to one another (e.g. causally, temporally, or with one event 'embedded' in another). The SemSpec also captures other kinds of event-related information, indicating, for instance, the participant's perspective from which the event is being described; this is more information than usually supplied by SR labeling systems.

Integration of FN data into ECG

In the current work, we focus on two complementary ways of using FN data to increase the coverage of ECG grammars. First, we examine how FN frames can be converted to ECG schemas, thus substantially increasing the breadth and depth of the ECG schema lattices. Second, we explore ways to generalize over FN valence patterns to build ECG argument structure constructions.

In order to facilitate this (semi-)automatic process, we had to extract and normalize the FN data, allowing us to create and view patterns that are not directly accessible through the existing FN-based tools. We developed a set of tools to read in and manipulate FrameNet data, which we then used to produce ECG schemas and constructions. As we discuss, while FrameNet and ECG share a similar conceptual foundation, there are some key differences that need to be considered when using FN data to expand the ECG grammar.

FN Frames and ECG Schemas

The hand-built ECG grammar contains lattices of embodied schemas, which focus primarily on schemas related to basic, relatively universal human experiences, such as goal-directed motion, acting on and manipulating objects, as well as basic kinds of entities and spatial relations. While some of the FN frames overlap those in ECG (e.g. **Motion**), FN also includes a large number of frames for a wide range of specific situations and entities. Thus, FN provides a means to substantially increase the conceptual coverage of ECG grammars.

FN Frames

FN frames are schematic representations of the conceptual structures associated with events, relations, and objects. As illustrated in Table 1 for **Cause_motion**, each frame contains frame elements (FEs) to represent internal frame structure. FEs are categorized with respect to their ‘coreness’ relation to the frame. For instance, in **Cause_motion**, FEs such as *Agent* and *Theme* are considered central to the frame’s meaning and are therefore marked as Core, whereas FEs such as *Manner* and *Distance* are considered less central to this specific frame, and are therefore marked as non-Core (i.e. Peripheral or Extra-Thematic). In some cases FN assigns a Semantic Type to an FE to indicate the basic type of the filler of this FE (e.g. *Agent* has Semantic Type: Sentient). Some FEs are mutually exclusive, captured via an ‘excludes’ relation.

	name	coreType	semtype	excludes
30	Agent	Core	Sentient	∅
31	Theme	Core	Physical_object	∅
32	Source	Core	Source	[Area]
33	Path	Core	None	[Area]
34	Goal	Core	Goal	[Area]
35	Distance	Peripheral	None	∅
36	Area	Core	None	∅
37	Depictive	Extra-Thematic	None	∅
38	Degree	Extra-Thematic	Degree	∅
39	Means	Peripheral	State_of_affairs	∅
40	Manner	Peripheral	Manner	∅
41	Subregion	Extra-Thematic	Locative_relation	∅
42	Cause	Core	None	[Agent]

Table 1. Partial list of FN *Cause_motion* frame elements.

FN uses several different relation types to capture frame-to-frame relations, as well as the relations between the FEs of the related frames. For instance, **Cause_motion** ‘Inherits from’ **Transitive_action**, and ‘Is Causative of’ **Motion**. Thus, individual FN frames are defined within larger frame lattices. Altogether, the frame lattice represents a network of world knowledge;

crucially, the structures in this network were hypothesized from corpora of actual language use.

Each frame also specifies a set of lexical units (LUs) which evoke that frame, thereby linking words to their frame-based meanings. For instance, **Cause_motion** lists 42 LUs, including *catapult*, *fling*, *hurl*, *move*, *nudge*, *shove*, and *transfer*.

Converting FN Frames to ECG Schemas

ECG schemas and FN frames were designed with different purposes in mind, but are largely structurally and functionally analogous, as shown in Table 2.

	FN frames	ECG schemas
Name	FN frame name	ECG schema name
Relations	Inherits from, Uses	subcase of, evokes
Elements	Frame elements (FEs)	roles
Constraints	Semantic type	ontological type
Internal relations	FE to FE relations	bindings

Table 2. Analogous terms in FrameNet and ECG

For example, inheritance relations are captured in FN via the ‘Inherits from’ relation and in ECG via the ‘subcase’ relation. The FNs ‘Uses’ relation is analogous to the ECG ‘evokes’ relation. One significant difference, though, is that there are several more ways to express relations between FN frames than between ECG schemas. For some FN relation types, the general ECG ‘evokes’ relation can suffice, but for others, such as ‘Precedes’ or ‘Perspective on’ it is not immediately clear how to represent the relation in ECG. Causal relations are also handled differently in FN and ECG. FN, for example, uses a ‘Is Causative of’ relation to capture the causal relation between **Cause_motion** and **Motion**, whereas ECG captures this causal relation via the incorporation of causal structure within its **CauseMotion** schema (Dodge and Petruck, 2014). For the current work, we chose to include only the FN ‘Inherits from’ and ‘Uses’ relations in the conversion process. But, in the longer term, some of the additional FN relations may prompt exploration of way to increase the expressiveness of the ECG formalism.

Using these analogous relations, we automatically converted FN frames to ECG schemas. Figure 1 shows the ECG schema generated from the FN **Cause_motion** frame. Inherited roles are listed in comments, which are introduced by double slashes (//), and any semantic type constraints on FN FEs are converted to ECG ontological type constraints (e.g. @physical_entity). The ‘constraints’ section of the ECG schema shows FE-to-FE relations as ECG role bindings, symbolized by the double-headed arrow (↔).

Using this model of frame-to-schema conversion, we were able to import 1205 frames into ECG. We used version 1.6 of FrameNet for this, but the conversion

model is general and should apply to other versions, assuming the frame representation stays consistent.

```

schema Cause_motion
  subcase of Transitive_action
  evokes Motion as motion
  roles
    // agent, cause, depictive, manner, means
    // place, result, time are inherited
    area
    degree: @degree
    distance
    explanation
    goal: @goal
    handle
    initial_state
    instrument: @physical_entity
    path
    source: @source
    subregion: @locative_relation
    theme: @physical_object
  constraints
    patient ↔ theme
    area ↔ motion.area
    degree ↔ motion.degree
    depictive ↔ motion.depictive
    distance ↔ motion.distance
    goal ↔ motion.goal
    manner ↔ motion.manner
    path ↔ motion.path
    result ↔ motion.result
    source ↔ motion.source
    theme ↔ motion.theme

```

Figure 1. The ECG Cause_motion schema produced from the FN Cause_motion frame

One of the other challenges of this process is integrating FN’s internally consistent hierarchy of frames with ECG’s internally consistent hierarchy of schemas. This is a general problem of combining ontologies; name-space collisions arise, as do differences in inheritance lattices. There is no immediately clear solution to this problem. For the purposes of this work, we used a scaled-down ECG grammar to prevent namespace and inheritance collisions.

FN Valence Patterns to ECG Constructions

Existing ECG grammars contain lattices of constructions for a wide range of basic clausal and phrasal constructions, including constructions for noun phrases, prepositional phrases, and basic types of clauses. The current work focuses on expanding the number and range of ECG Argument Structure (A-S) constructions, which generally specify patterns by which a verb and its arguments are used to describe a particular event and its participant roles. Specifically, we focus on the ways that valence pattern information recorded in FN annotation

data can potentially be used to generate A-S constructions.

FN data is in many ways well-suited to this task. First, FN frames are quite typically defined with respect to events and event participants, thus corresponding directly to the kinds of semantic information expressed by A-S constructions. Consequently, ECG A-S construction meaning can readily be specified by ECG schemas and roles that have been derived from FN frames and FEs. Second, the FN valence pattern information recorded for a given verb target is essentially a specification of a particular argument realization pattern associated with that verb.

However, as we describe more fully below, there are some complicating factors. For instance, a given sentence typically instantiates many different constructions, and the annotation for that sentence may therefore reflect more than one constructional pattern. Also, constructions can potentially be specified at different levels of schematicity, though in a usage-based approach, specific and more general constructions can co-exist.

In the following sections, we first discuss FN annotation and valence patterns, and then present a simple method of generating ECG A-S constructions from this information. Following this, we discuss the complicating factors and ways to handle them, by filtering and other methods.

FN Annotation and Valence Patterns

In addition to defining frames and sets of LUs that evoke these frames, FN annotates sentence examples containing these LUs, with the objective of demonstrating the different patterns by which frames and frame elements are expressed in language. Sentences are annotated with respect to target words (LUs) and the FEs expressed by the syntactic dependents of that target. For each of these constituents, three kinds of information are recorded:

1. FE: the frame element it instantiates (e.g. *Theme*)
2. PT: its phrase type (e.g. NP)
3. GF: its grammatical function (e.g. Object)

When the target is a verb, three types of GF are possible:

- External argument (Ext): e.g., the subject of a finite verb
- Object (Obj): objects, typically those which can also occur as subjects of passive clauses
- Dependent (Dep): the grammatical function assigned to adverbs, PPs, VPs and clauses that typically occur after the verb in declarative sentences.

FN data includes two kinds of annotation. In lexicographic annotation, FN annotates example sentences with respect to a single LU target, serving to illustrate the valence patterns for the LUs associated with a given frame. In full annotation of running text, FN

identifies all the frame-evoking target words in a given sentence, along with the FEs expressed by each of them. The current work examines lexicographic annotation.

FN valence patterns

FN valence patterns, as displayed in FN Lexical Entry reports, are sets of FE realizations (FE/PT/GF triples) that co-occur in the lexicographic annotations for a given LU. Thus, for any given LU, an individual valence pattern indicates how a set of frame elements are instantiated grammatically, as evidenced in one or more example sentence annotations. Table 3 shows the valence pattern displayed for a sentence such as example (1). Note that the FN display lists the FE realizations in the alphabetical order of the FEs, not in the order that they occur in the sentence.

FE:	<i>Agent</i>	<i>Goal</i>	<i>Theme</i>
PT:	NP	PP[into]	NP
GF:	Ext	Dep	Obj

Table 3. Valence pattern for “The boy threw the ball into the pool.”

Using FN Data to Define ECG Constructions

Our general strategy for using FN data is as follows. For each frame, consider the set of valence patterns, and:

1. Filter out LU targets that have POS other than verb, since our focus is on ‘verb plus argument’ A-S constructions (verb plus its FE arguments)
2. Remove non-core FEs from valence patterns. This is done because the valence patterns for core FEs are the best indicator of frame-specific A-S constructions. Non-core FEs may best be handled via separate constructions. *Manner*, for instance, can be handled via a separate modifier construction that can compose with many different A-S constructions.
3. Ignore null-instantiated FEs; for the current work we focus on FEs that are explicitly expressed.

Using this initial data set, we can explore various methods for identifying candidate argument realization patterns for ECG construction generation.

Simple Case: 1-1 Mapping

The simplest generation method directly maps FNs valence patterns to ECG constructions. As represented in Table 3, FN valence patterns already abstract away from the specific text strings that express these FEs, as well as the order in which the FEs occur in the sentences. Consequently, when two or more sentences exhibit the same set of FE realizations, they can be considered instances of the same valence pattern.

It is fairly straightforward to represent an FN valence pattern as an ECG A-S construction. The meaning of the construction as a whole is identified with the ECG schema that was derived from the FN frame. The verb and

non-external arguments (i.e. those whose GF is either Obj or Dep) will be used to define the construction’s constituents, with the PTs serving to estimate the constituent’s constructional type (e.g. NP). Bindings between the meanings of these constituents and the schema roles serve to specify which role (FE) is being expressed by each constituent. The external argument (e.g. a subject) is handled differently than the other arguments. ECG A-S constructions are a type of verb phrase, and therefore do not include a subject constituent. But, as part of their meaning, they evoke a *profiled-participant* role, which is, roughly speaking, the semantic correlate of subject. Consequently, we implemented a general rule to bind the FE expressed by **Ext** to this *profiled-participant* role. See Figure 2 for an example of a construction generated using this algorithm.

```

construction Cause_motion_pattern_10
  subcase of ArgumentStructure

constructional
  constituents
    v: Verb
    pp-into: PP-Into
    np: NP

  meaning: Cause_motion
  constraints
    self.m ↔ v.m
    profiledParticipant ↔ self.m.agent
    self.m.goal ↔ pp-into.m
    self.m.theme ↔ np.m

```

Figure 2. A-S construction generated from FN valence pattern

The lexicographic annotation data for **CauseMotion** includes 821 sentence examples, which exhibit 598 unique valence patterns. If we use a method that generates an ECG construction for each FN valence pattern, we would thus generate a very large number of constructions. More importantly, this method ignores any commonalities across the different valence patterns, and thus does not capture broader generalizations about language use.

We can significantly reduce this number by generalizing over the specific verbs that appear in these patterns. Moreover, it is straightforward to define ECG constructions that make this generalization, by binding the meaning of the verb to the meaning of the A-S construction (self.m ↔ v.m). Thus, for the construction depicted in Figure 2, any verb whose meaning is identified with the **Cause_motion** schema (i.e. all the LUs in the **Cause_motion** frame) will be able to serve as the verb constituent in this construction. Making this generalization over verbs enables us to reduce the total number of constructions to 258. While this is an improvement, in the following section we discuss ways that we can further reduce the number of constructions needed to analyze these FN valence patterns.

Further Exploration of FN Data

In this section, we examine some ways to further explore the FN data, draw generalizations, and define additional constructions to capture the patterns exhibited by the FN annotated sentences. We start by looking for broad generalizations in the argument realization patterns for a given frame, with the objective of identifying relatively general patterns in which the number, GF and FE of the constituents are the same. Then, based on these initial findings, we examine how other patterns in that frame may be fruitfully analyzed using an ECG compositional analysis, in which frame-specific A-S constructions compose with other, more language-general constructions.

Because constituent ordering is an important feature of English A-S constructions, we are interested in the ordering in which the verb's arguments are expressed. We divided the data into categories based on the type and order of grammatical functions of the core FEs expressed in a given sentence. Two general GF sequence pattern categories account for the majority of the 821 examples in the filtered Cause_motion data:

1. **Ext v Obj Dep+** (55.8% of the data)
2. **Ext v Dep+** (20.3% of the data)

The plus sign here has the usual meaning of “one or more instances of”. Therefore the first pattern describes instances of annotations in which Ext is followed by the target verb, then the object Obj and one or more dependents.

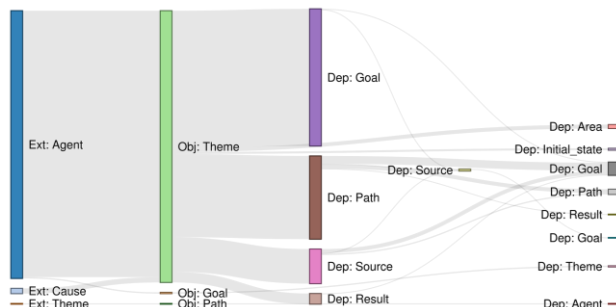


Figure 3. Flow diagram for *Ext* → *v* → *Obj* → *Dep+* patterns

Figures 3 and 4 present Sankey flow diagrams of these two categories. The nodes (horizontal bars) in the diagram represent GF/FE pairs (e.g. Ext: *Agent*), with size proportional to relative frequency. The nodes are arrayed from left to right in their linear order of occurrence in sentence example (e.g. Ext: *Agent* → Obj: *Theme*). The width of the connections between nodes indicates the relative number of examples exhibiting that pattern. When we look at these patterns with respect to the FEs associated with each of these GFs, some clear patterns become apparent.

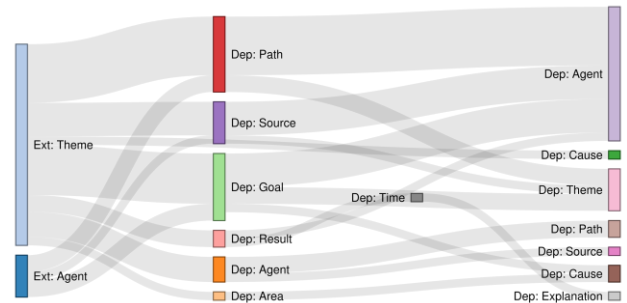


Figure 4. Flow diagram for *Ext* → *v* → *Dep+* patterns

The most commonly occurring pattern for the first sequence is: **Ext: Agent** → [verb] → **Obj: Theme** → **Dep: Goal**. This pattern suggests that rather than defining different A-S cxns for specific PP constituents (e.g. PP-into, as in previous cxn), we should instead define more general PP constituents, such as more general Goal, Path, and Source PPs. Following such an approach, we can define a more general A-S construction that is consistent with this frequent pattern (see Figure 5). This construction differs from the previous one in two key ways: (1) rather than having a relatively specific ‘pp-into’ constituent, it has a more general ‘goal-pp’ constituent, and; (2) it includes a ‘form’ block that specifies the ordering of the different constituents. This construction captures the patterns expressed in examples such as *He threw/tossed/catapulted the ball into/onto/to the box*.

```

construction Cause_motion_pattern_1A
  subcase of ArgumentStructure

contructional
  constituents
    v: Verb
    np: NP
    goalPP: Goal_PP

  form: v > np > goalPP

  meaning: Cause_motion
  constraints
    self.m ↔ v.m
    profiledParticipant ↔ self.m.agent
    self.m.goal ↔ goalPP.m
    self.m.theme ↔ np.m
  
```

Figure 5. A-S construction with goal-PP constituent

For the second sequence (as shown in Figure 4), the most frequent pattern is similar to that of the first sequence, in that it also expresses the Goal (**Ext: Theme** → [verb] → **Dep: Goal**). Thus, the main distinction between the two most frequent patterns in these two data sets concerns the different ways that the *Agent* and *Theme* are expressed, with the different patterns clearly corresponding to an active/passive distinction, which is part of a much more general language pattern. Consequently, rather than defining separate A-S constructions for these two patterns, it is preferable to

define a single construction that generalizes over the two patterns. This construction can then compose with much more general Active and Passive VP constructions, which is a method employed in existing ECG grammars to analyze passive and active expressions.

In both data sets, in addition to expressing *Goal*, *Dep* frequently expresses *Path* and/or *Source*, all of which are FEs used to indicate the spatial location of the *Theme*. In ECG, these three FEs are analyzed as part of a larger gestalt, represented as a **SourcePathGoal** schema, which enables generalizations over instances that in FN are split into three separate cases. In this way, image-schematic structure present in ECG facilitates generalizations that are not necessarily immediately apparent in FN.

We can also potentially make generalizations that are related to the ‘excludes’ relations between FEs. For instance, in Figure 3 we see that *Agent* and *Cause* are the two FEs most commonly expressed by the *Ext* argument, and that both occur as part of similar sequences. Since these two FEs are in an ‘excludes’ relation (as shown in Table 1), they are essentially alternatives to one another. Given the current structure of ECG, two different constructions are needed to capture the patterns associated with each of these FEs. However, it is also possible to abstract over these patterns by making them subcases of a more general supertype construction.

The most common patterns present in the remainder of the data are displayed in Table 4. In some cases, the patterns reflect the interaction of other constructions with the main A-S construction pattern. For instance, annotation of relative clauses typically results in duplicate FE realization patterns (e.g. *Ext: Agent* → *Ext: Agent*). This is the case for patterns number 9 and 10 in Table 4, which are, respectively, linked to phrases such as *a large envelope which he threw onto the table* and *a powerful weapon which can hurl its bolt*. By treating the duplicates as two instances of the same element, we can identify similarities between these and other patterns in the data.

	freq.	Patterns
1	18	Ext: Agent (NP) → v → Dep: Goal (PP) → Obj: Theme (NP)
2	11	v → Obj: Theme (NP) → Dep: Goal (PP) → CNI: Agent (None)
3	11	Ext: Agent (NP) → v → Dep: Source (PP) → Obj: Theme (NP)
4	11	Ext: Agent (NP) → v → Dep: Goal (AVP) → Obj: Theme (NP)
5	7	Ext: Agent (NP) → v → Obj: Theme (NP) → INI: Goal (None)
6	7	v → Dep: Goal (PP) → Obj: Theme (NP) → CNI: Agent (None)
7	6	v → Obj: Theme (NP) → Dep: Path (PP) → CNI: Agent (None)
8	5	v → Obj: Theme (NP) → Dep: Source (PP) → CNI: Agent (None)
9	5	Ext: Agent (NP) → Ext: Agent (NP) → v → Obj: Theme (NP) → Dep: Path (PP)
10	5	Obj: Theme (NP) → Obj: Theme (NP) → Ext: Agent (NP) → v → Dep: Goal (PP)
11	5	Ext: Agent (NP) → v → Dep: Path (PP) → Obj: Theme (NP)

Table 4. Patterns with five or more instances in ‘Other’ data set. in descending frequency (‘fr.’) order.

Imperatives also produce another pattern, with the *Agent* FE appearing as *CNI* rather than as *Ext*, which is

consistent with patterns 2, 7, and 8 (which contain examples such as *Do not fling me from your house!*). Similar to passives, ECG uses a more general Imperative construction that composes with different A-S constructions to analyze imperative sentences.

This same approach can be readily applied to other frames, enabling comparison of patterns across related frames. For instance, **Cause_fluidic_motion** is a subcase of **Cause_motion**. We can see the similarity between the most frequently occurring patterns for these two frames (as shown in Figures 4 and 6), given that the **Cause_fluidic_motion** *Fluid* FE is a more specific case of the **Cause_motion** *Theme* FE.

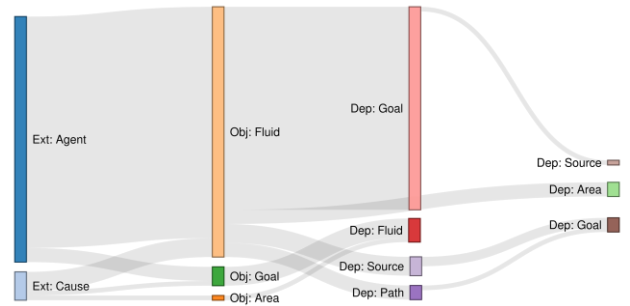


Figure 6. Flow diagram for *Cause_fluidic_motion*, *Ext* → *v* → *Obj* → *Dep*+ patterns

In sum, we can see that there are many ways to explore the FN data, and to use it to identify the kinds of interacting patterns and generalizations that are relevant to the development of A-S constructions. While this initial work has focused on the FN **Cause_motion** frame and its lexicographic annotations, the methods described here have been designed to be applicable to any frame, or combination of related frames.

Future Directions

The next step is to extend and refine the present work in order to use the entirety of the FN data to automatically generate A-S and other constructions (e.g. nominal and prepositional phrase constructions). As part of this process, we will iteratively evaluate and refine the resulting ECG grammar by applying it to the analysis of real world data. One possible avenue for evaluation is to use the FN full-text annotations as a ‘gold standard’ set for testing the accuracy of the annotation produced via ECG analysis. During this process it is important to keep in mind that FN data is not intended to be statistically representative of actual language usage frequencies, and therefore does not supply optimal distributional information.

While FN data provides a way to substantially increase the coverage of an ECG grammar, this approach is ultimately limited by the coverage of FN itself (Palmer and Spolleder 2010). Thus, even if we succeed in

generalizing ECG schemas and constructions across the entire FN database, there will still be many utterances that cannot be fully parsed due to gaps in constructional coverage.

Therefore, additional steps will be needed to further expand the grammar. One possible way to address this constraint is to expand FN coverage using machine learning. This might be accomplished starting with methods such as those described by Pennacchiotti et al. (2008), who induce new adjectives and verbs using word similarity based on distributional semantics. Ultimately, we would also like to investigate how the constructional parsing methods we develop can themselves help in this task of expanding FN.

It is also important to note that FN is not necessarily designed to contain all the types of semantic information and constructional patterns needed to create a comprehensive grammar of English (McCauley and Christiansen 2014). Therefore, some conceptual and constructional gaps in the grammar will have to be filled by other means. Previous work in learning ECG constructions (Chang 2008, Mok 2009) provide some possible future directions in this regard.

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