ENLP Lecture 19
Semantic Role Labeling and Argument Structure

Nathan Schneider

16 November 2016

Language is flexible.

I'm thrilled to visit sunny California.

I'm thrilled to visit California, where the weather is sunny.

I'm thrilled to visit California, where it's sunny.

I'm excited to visit California, where it's sunny.

I'm excited to visit California, where it's sunny out.

I'm excited to spend time in California, where it's sunny out.

I'm not excited to visit sunny California.

I'm thrilled to visit sunny Florida.

I'm thrilled to visit sunny Mountain View.

I'm thrilled to visit California because it's sunny.

I'm sort of happy about the California visit.

나는 맑은 캘리포니아를 방문 기뻐요. אני נרגש לבקר קליפורניה שטופת שמש.

Lexical Semantics

- So far, we've seen approaches that concern the **choice** of individual words:
  - sense disambiguation
  - semantic relations in a lexicon or similarity space
- Today: words that are fully understood by **"plugging in"** information from elsewhere in the sentence.
  - Specifically, understanding words that are (semantic) **predicates**, in relation to their **arguments**.
  - Especially **verbs**.
  - *Who did what to whom?*

Argument Structure Alternations

- Mary opened the door.
  The door opened.

- John slices the bread with a knife.
  The bread slices easily.
  The knife slices easily.

- Mary loaded the truck with hay.
  Mary loaded hay onto the truck.
  The truck was loaded with hay (by Mary).
  Hay was loaded onto the truck (by Mary).

- John got Mary a present.
  John got a present for Mary.
  Mary got a present from John.

Stanford Dependencies

- Mary loaded the truck with hay.

  nsubj *dobj* *prep_with*

- Hay was loaded onto the truck by Mary.

  nsubj_pass *prep_onto* *prep_by*

Stanford Dependencies

- Mary loaded the truck with hay.

nsubj dobj
prep_with

- Hay was loaded onto the truck by Mary.

nsubj_pass prep_onto
prep_by

Syntax is not enough!

Syntax-Semantics Relationship

Outline

- Syntax ≠ semantics
  - The **semantic roles** played by different participants in the sentence are not trivially inferable from syntactic relations
  - …though there are patterns!
- Two computational datasets/approaches that describe sentences in terms of semantic roles:
  - PropBank — simpler, more data
  - FrameNet — richer, less data
- The idea of semantic roles can be combined with other aspects of meaning. Glimpse of **AMR**, which is one way to do this.

PropBank

- Abstracts away from syntax to predicate-argument structures

PropBank

Mary loaded the truck with hay at the depot on Friday.

- *load*: load.01 ‘cause to be burdened’
  Roles:
    Arg0-PAG: loader, agent
    Arg1-GOL: beast of burden
    Arg2-PPT: cargo
    Arg3-MNR: instrument

- *load_up*: load.02 ‘phrasal cause to be burdened’

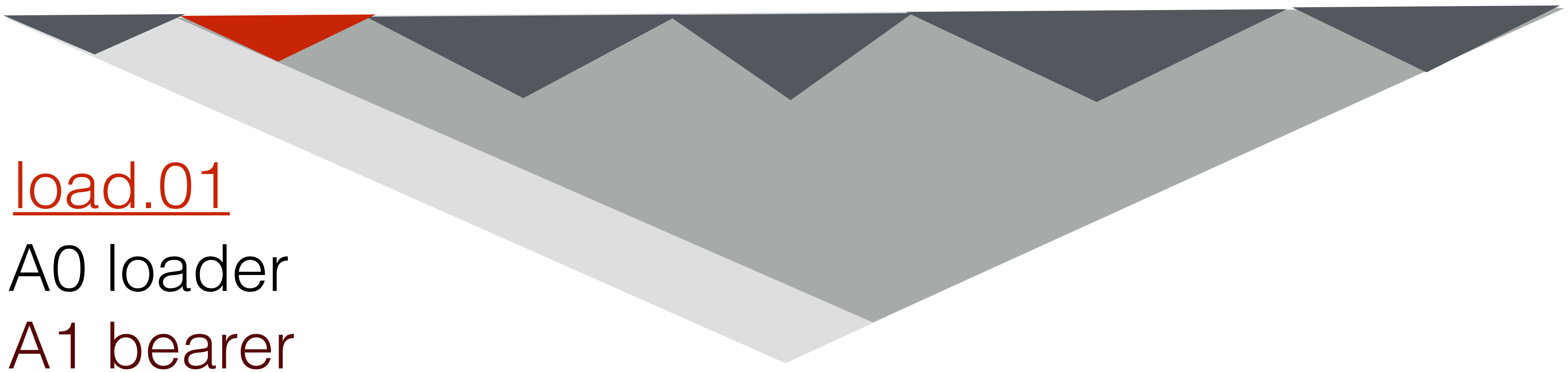
- *load*: load.03 ‘fix, set up to cheat’

PropBank

Mary loaded the truck with hay at the depot on Friday.

PropBank

Mary **loaded** the truck with hay at the depot on Friday.



load.01

A0 loader

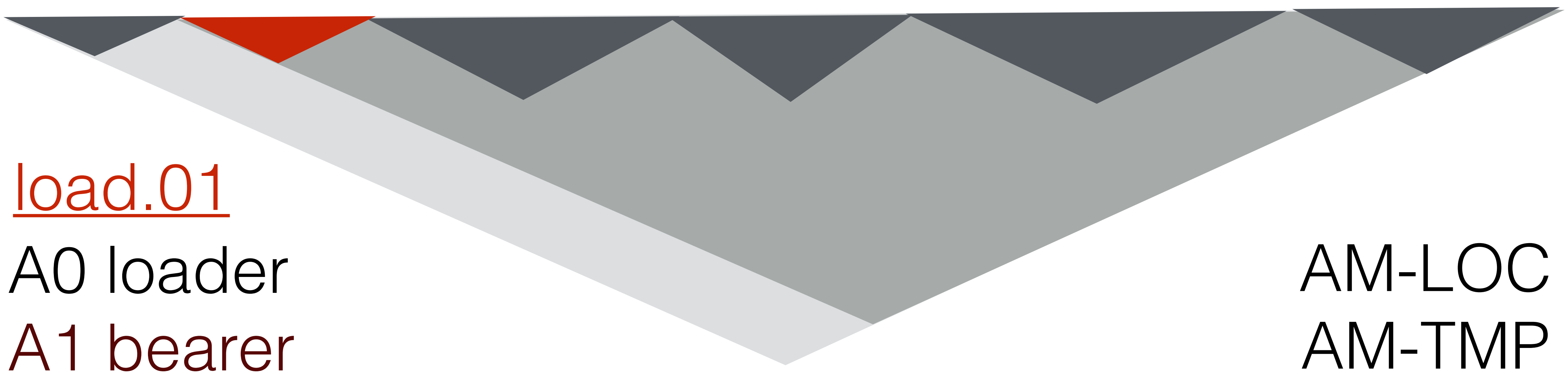
A1 bearer

A2 cargo

A3 instrument

PropBank

Mary **loaded** the truck with hay at the depot on Friday.



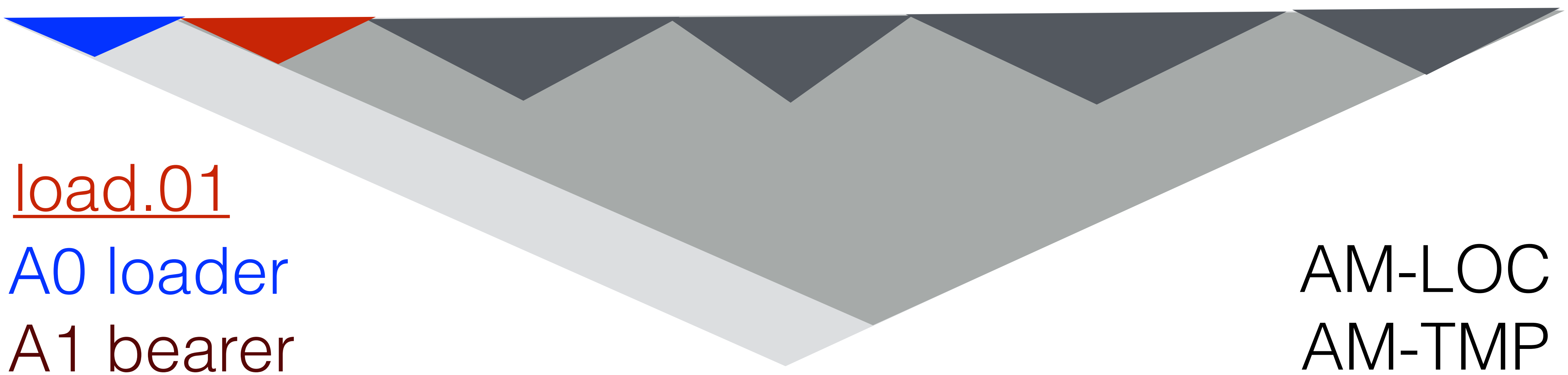
load.01

A0 loader
A1 bearer
A2 cargo
A3 instrument

AM-LOC
AM-TMP
AM-PRP
AM-MNR
…

PropBank

Mary **loaded** the truck with hay at the depot on Friday.



load.01

A0 loader

A1 bearer

A2 cargo

A3 instrument

AM-LOC

AM-TMP

AM-PRP

AM-MNR

…

PropBank

Mary **loaded** the truck with hay at the depot on Friday.

load.01

A0 loader

A1 bearer

A2 cargo

A3 instrument

AM-LOC

AM-TMP

AM-PRP

AM-MNR

…

PropBank

Mary **loaded** the truck with hay at the depot on Friday.

load.01

A0 loader

A1 bearer

A2 cargo

A3 instrument

AM-LOC

AM-TMP

AM-PRP

AM-MNR

. . .

PropBank

Mary **loaded** the truck with hay at the depot on Friday.

load.01

A0 loader

A1 bearer

A2 cargo

A3 instrument

AM-LOC

AM-TMP

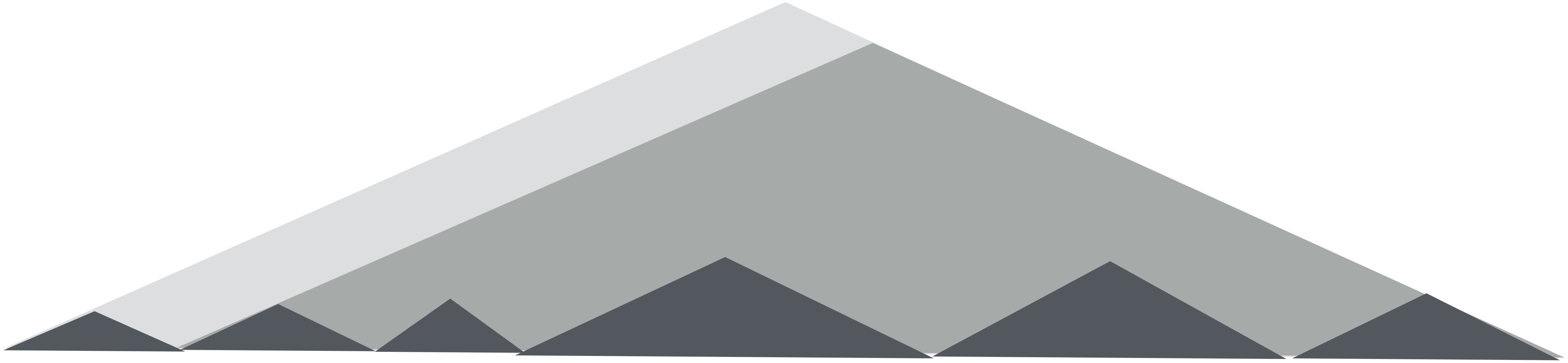
AM-PRP

AM-MNR

...

PropBank

Mary **loaded** the truck with hay at the depot on Friday.



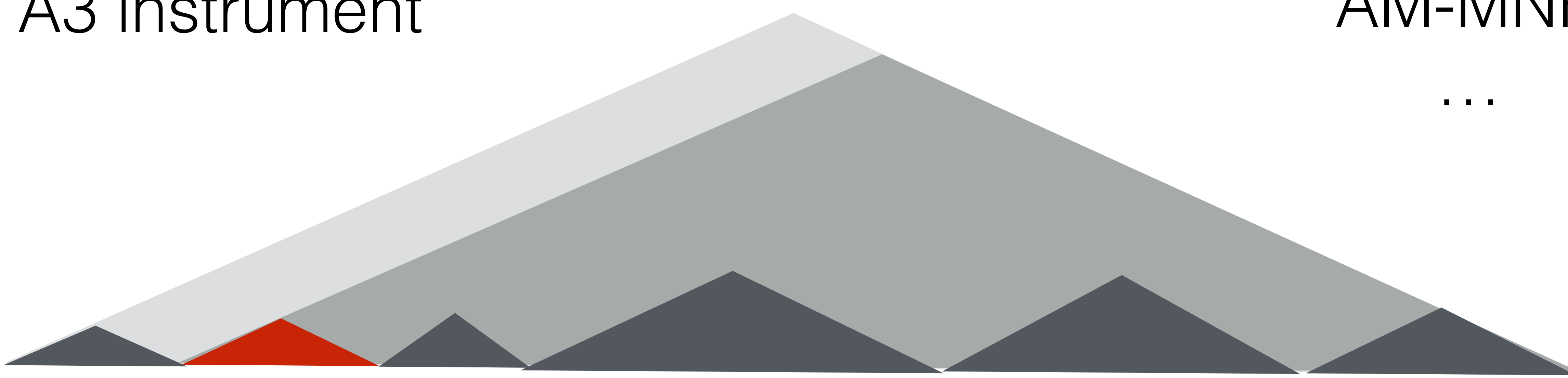
Mary loaded hay onto the truck at the depot on Friday.

PropBank

Mary **loaded** the truck with hay at the depot on Friday.

load.01
A0 loader
A1 bearer
A2 cargo
A3 instrument

AM-LOC
AM-TMP
AM-PRP
AM-MNR
…



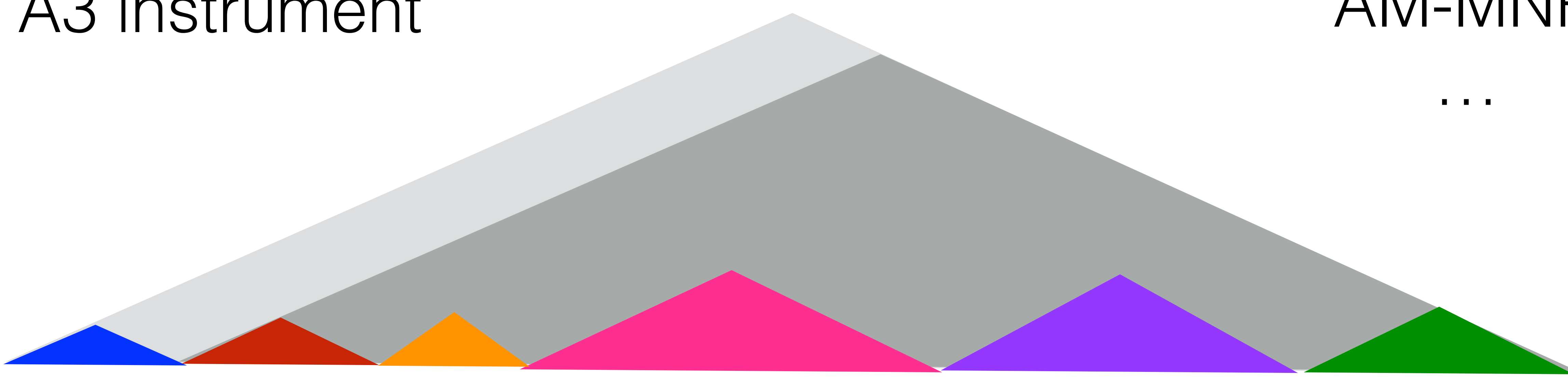
Mary **loaded** hay onto the truck at the depot on Friday.

PropBank

Mary **loaded** the truck with hay at the depot on Friday.

load.01
A0 loader
A1 bearer
A2 cargo
A3 instrument

AM-LOC
AM-TMP
AM-PRP
AM-MNR
…



Mary **loaded** hay onto the truck at the depot on Friday.

PropBank

- Abstracts away from syntax to predicate-argument structures
- Predicate-argument lexicon + annotations of full WSJ PTB corpus and other data (such as OntoNotes)
- Originally **verbs** only (Kingsbury & Palmer 2002); now has many nouns, adjectives, light verb constructions, etc. (Bonial et al. 2014)
- Strongly **lexicalized**: no synonymy, hypernymy, etc. of predicates with different stems; very coarse-grained sense distinctions
- Phrase structure constituents of PTB(-style) trees

Argument Structure Alternations

- Mary opened the door.
  The door opened.

- John slices the bread with a knife.
  The bread slices easily.
  The knife slices easily.

- Mary loaded the truck with hay.
  Mary loaded hay onto the truck.
  The truck was loaded with hay (by Mary).
  Hay was loaded onto the truck (by Mary).

- John got Mary a present.
  John got a present for Mary.
  Mary got a present from John.

PropBank

Semantic Role Labeling

- Traditional pipeline:

  1. (Assume syntactic parse and predicate senses as given)

  2. **Argument identification:** select the predicate's argument phrases

  3. **Argument classification:** select a role for each argument

     useful feature: predicate →* argument path in tree

- See Palmer et al. 2010 for a review

Limitation of PropBank

- Numbered roles (ARG0, ARG1, etc.) are predicate-specific.
  - load.ARG1: beast of burden, whereas
  - put.ARG1: thing put
  - load.ARG1 corresponds to put.ARG2

Thematic Roles

- Linguists talk about general classes of semantic roles:
  - *Agent* = animate entity who is volitionally acting
  - *Theme* = participant that is undergoing motion, for example
  - *Patient* = participant that undergoes some internal change of state (e.g., breaking)
  - *Destination* = intended endpoint of motion
  - *Recipient* = party to which something is transferred
- The **VerbNet** resource uses these and a couple dozen other roles.
- But it is hard to come up with a small list of these roles that will suffice for all verbs.
- And there are correspondences that these roles do not expose: e.g., that someone who *buys* is on the receiving end of *selling.*

Berkeley FrameNet

https://framenet.icsi.berkeley.edu/

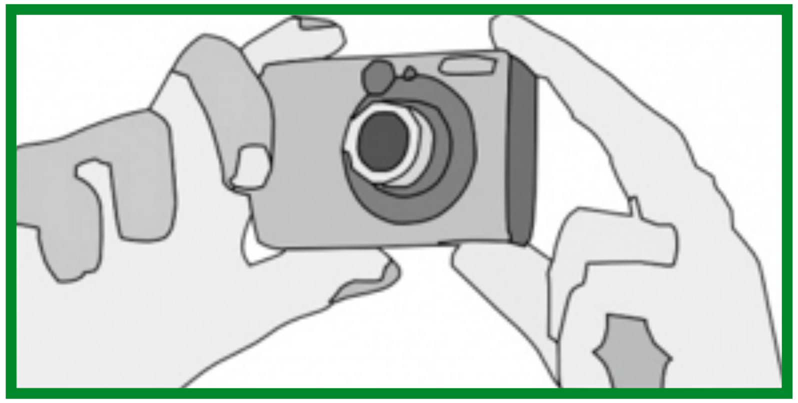
Paraphrase

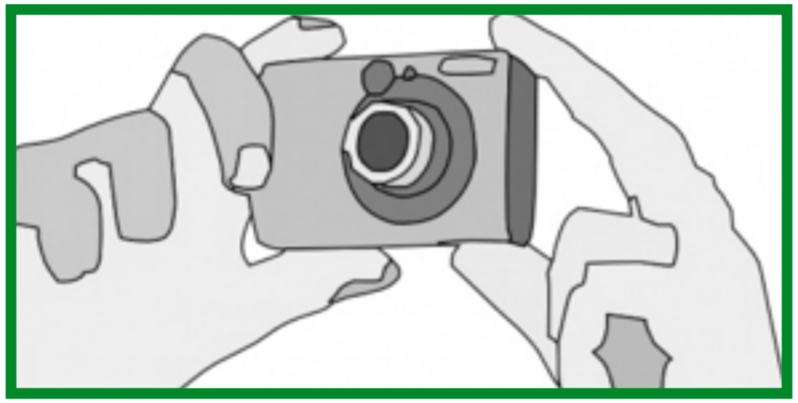
- James snapped a photo of me with Sheila.

- Sheila and I had our picture taken by James.

What's in common

- James **snapped a photo** of me with Sheila.

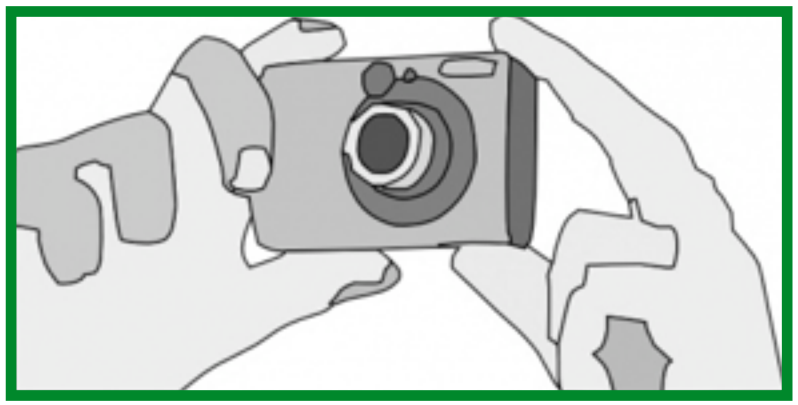




- Sheila and I had our **picture taken** by James.

What’s in common

- James **snapped a photo** of me with Sheila.



- Sheila and I had our **picture taken** by James.

Idealized Stanford Dependencies

- James snapped a photo of me with Sheila.

  nsubj(snap, James)
  dobj(snap, photo)
  prep_of(photo, me)
  prep_with(me, Sheila)
  det(photo, a)

- Sheila and I had our picture taken by James.

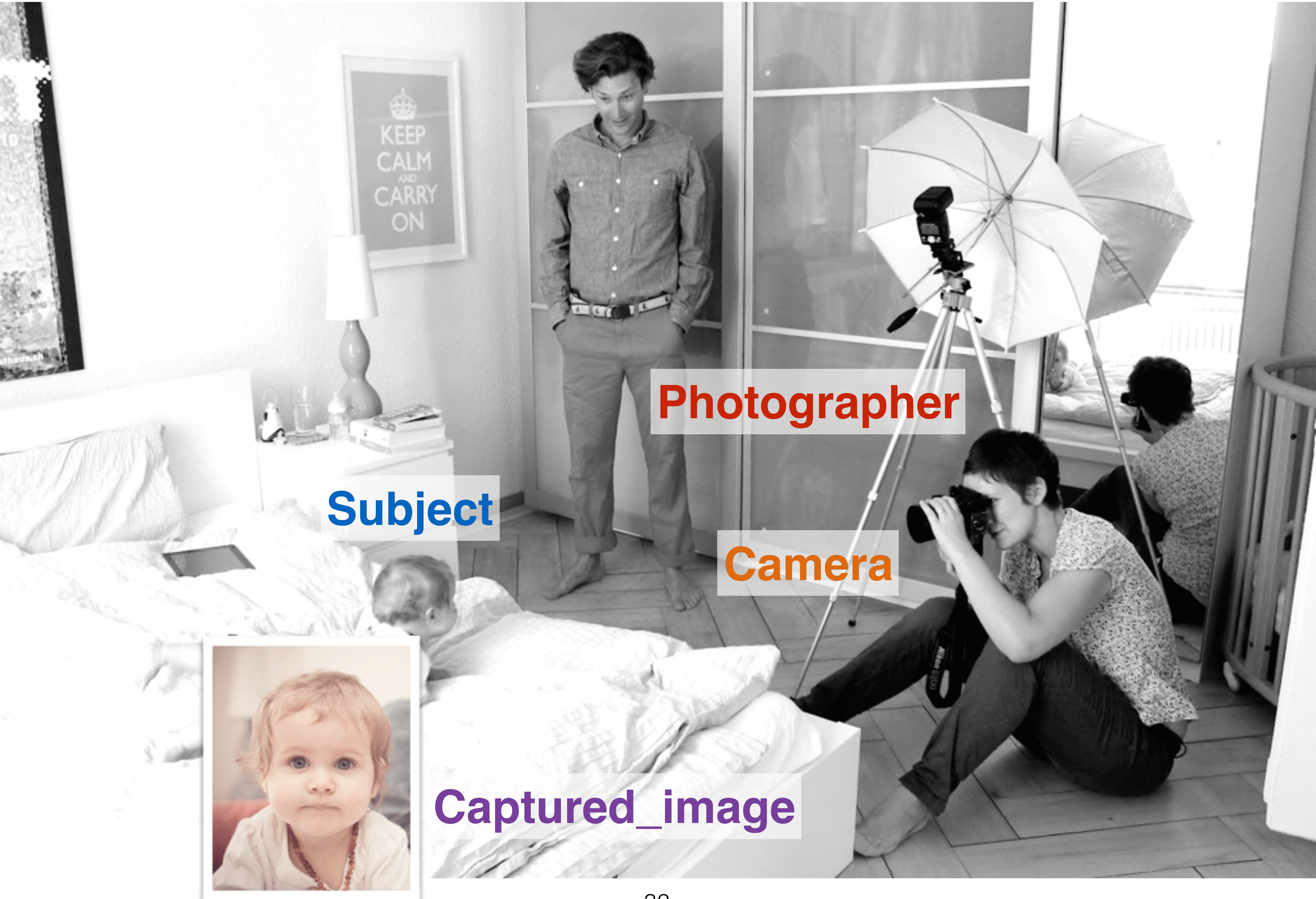
  nsubjpass(taken, Sheila)
  nsubjpass(taken, I)
  conj_and(Sheila, I)
  aux(taken, had)
  dobj(taken, picture)
  poss(picture, our)
  agent(taken, James)

Frame Semantics

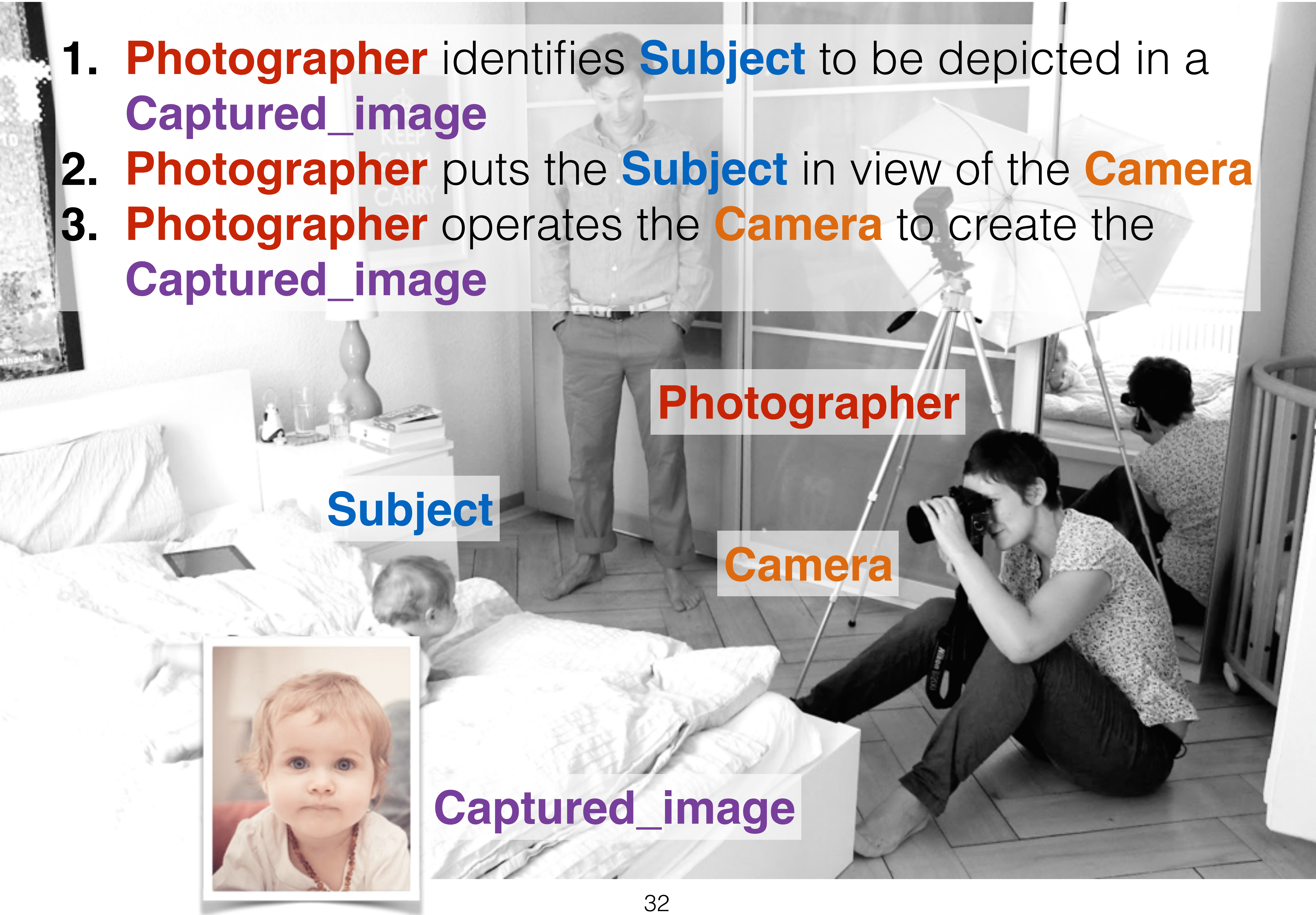
"MEANINGS ARE RELATIVIZED TO SCENES"

(Fillmore 1977)

http://www.swisslark.com/2012/08/jana-manja-photography-special-offer_29.html


KEEP
CALM
AND
CARRY
ON
Photographer
Subject
Camera
Captured_image

1. **Photographer** identifies **Subject** to be depicted in a **Captured_image**
2. **Photographer** puts the **Subject** in view of the **Camera**
3. **Photographer** operates the **Camera** to create the **Captured_image**



1. **Photographer** identifies **Subject** to be depicted in a **Captured_image**
2. **Photographer** puts the **Subject** in view of the **Camera**
3. **Photographer** operates the **Camera** to create the **Captured_image**

Photographer

Subject

Camera

Captured_image

1. **Photographer** identifies **Subject** to be depicted in a **Captured_image**
2. **Photographer** puts the **Subject** in view of the **Camera**
3. **Photographer** operates the **Camera** to create the **Captured_image**

	Photographer	
time	**Subject**	**manner**
duration	**Camera**	**location**
frequency	**Captured_image**	**reason**

1. **Photographer** identifies **Subject** to be depicted in a **Captured_image**
2. **Photographer** puts the **Subject** in view of the **Camera**
3. **Photographer** operates the **Camera** to create the **Captured_image**

Photographer

time	**Subject**	**manner**
duration	**Camera**	**location**
frequency	**Captured_image**	**reason**

photograph.v take ((picture)).v snap picture.v

frame name

textual definition explaining the scene and how the **frame** **elements** relate to one another

Core

Frame

Elements

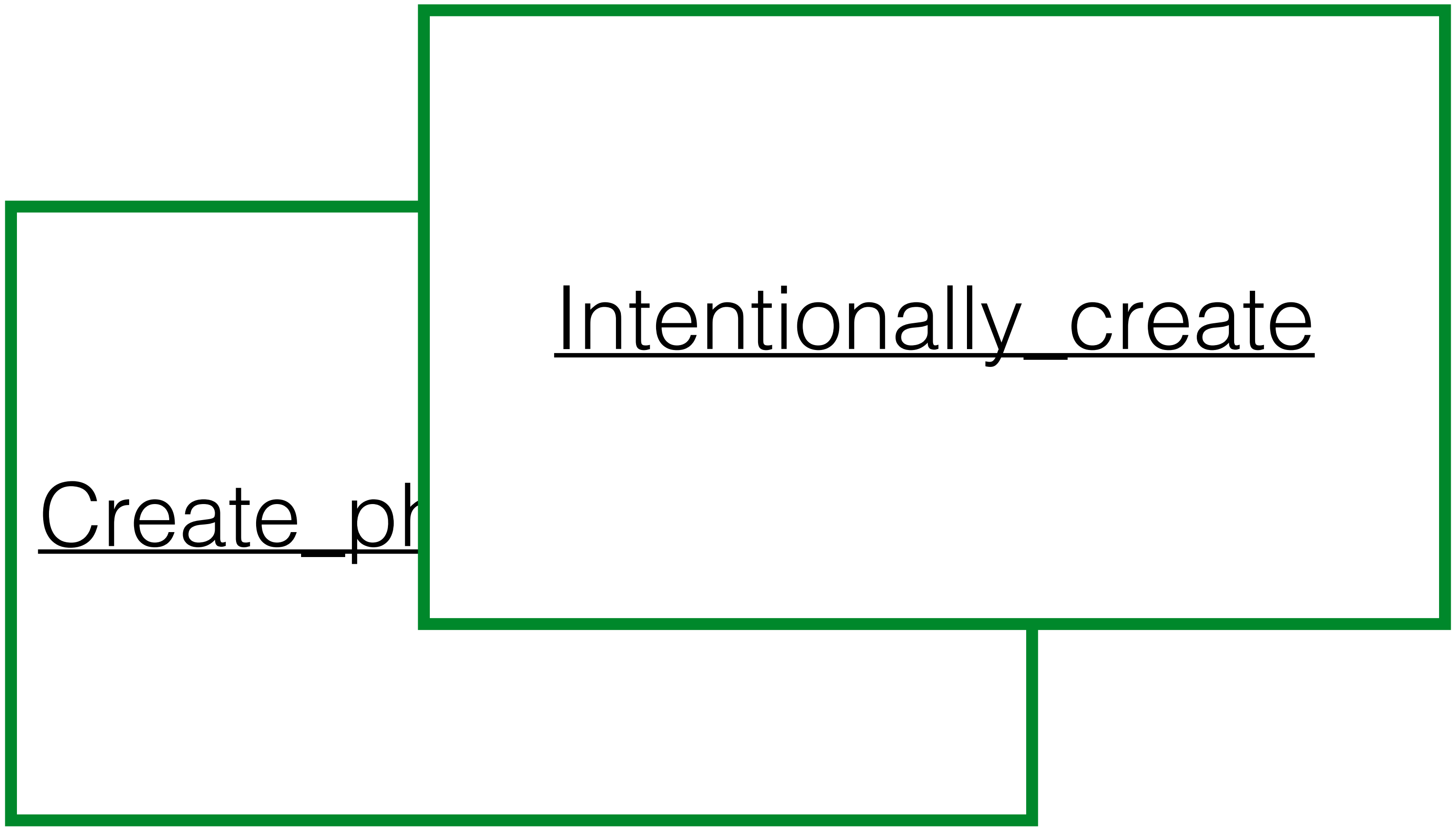
non-core

FEs

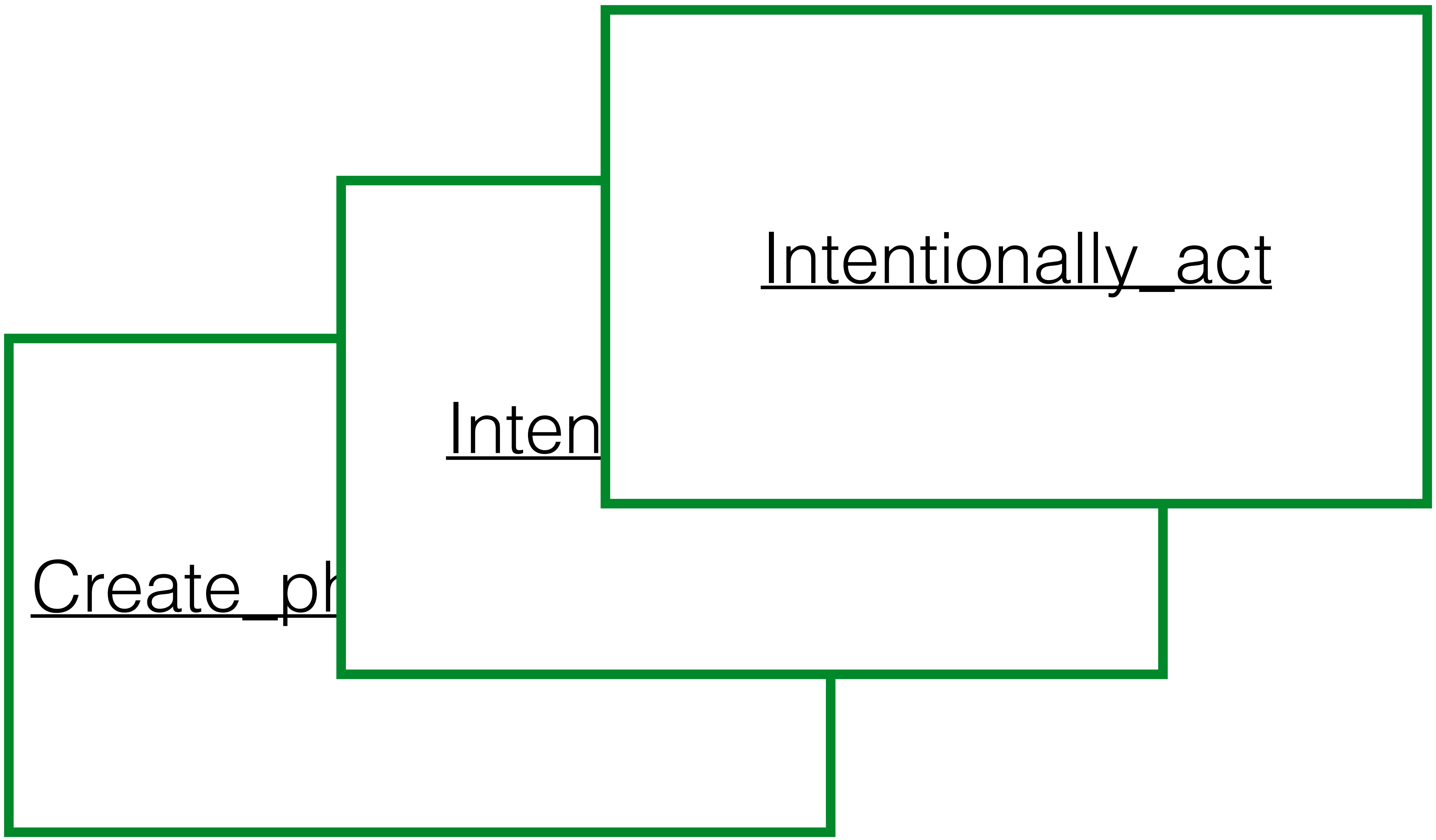
predicate1.v ***predicate2.n*** ***predicate3.a***

Create_physical_artwork

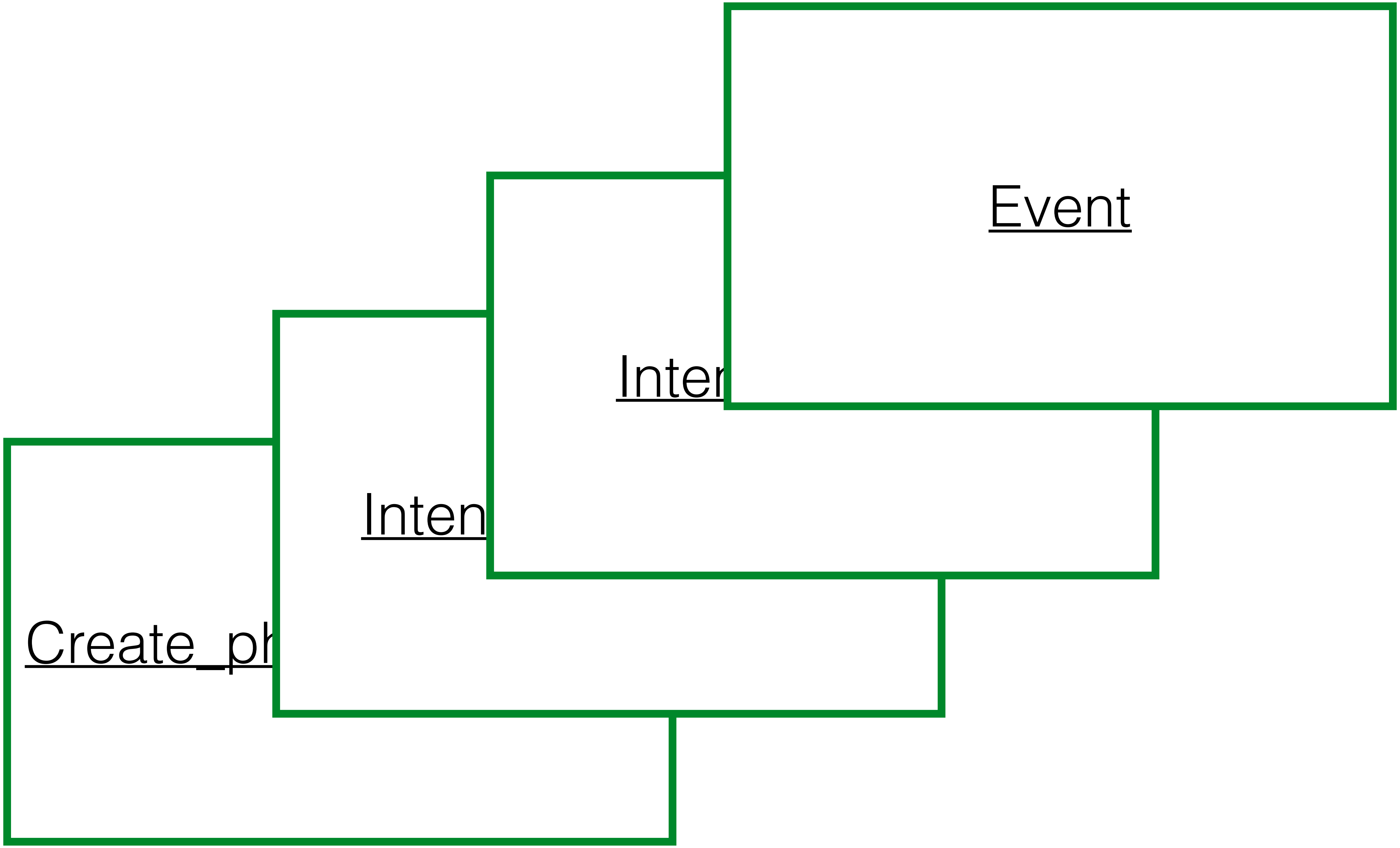
FrameNet



FrameNet



FrameNet



FrameNet

Create_physical_artwork

FrameNet

Create_physical_artwork

Physical_artworks

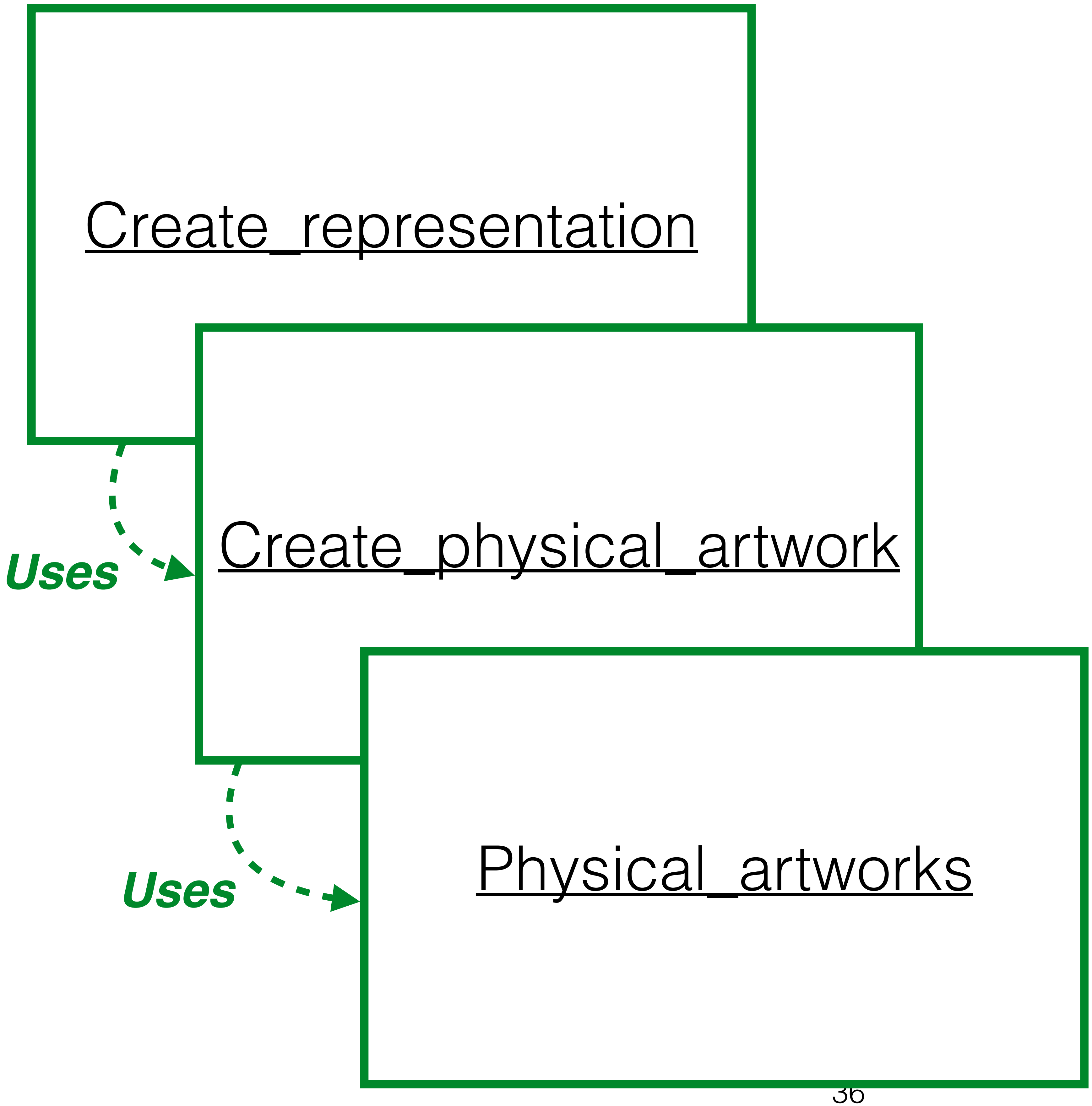
FrameNet

Create_representation

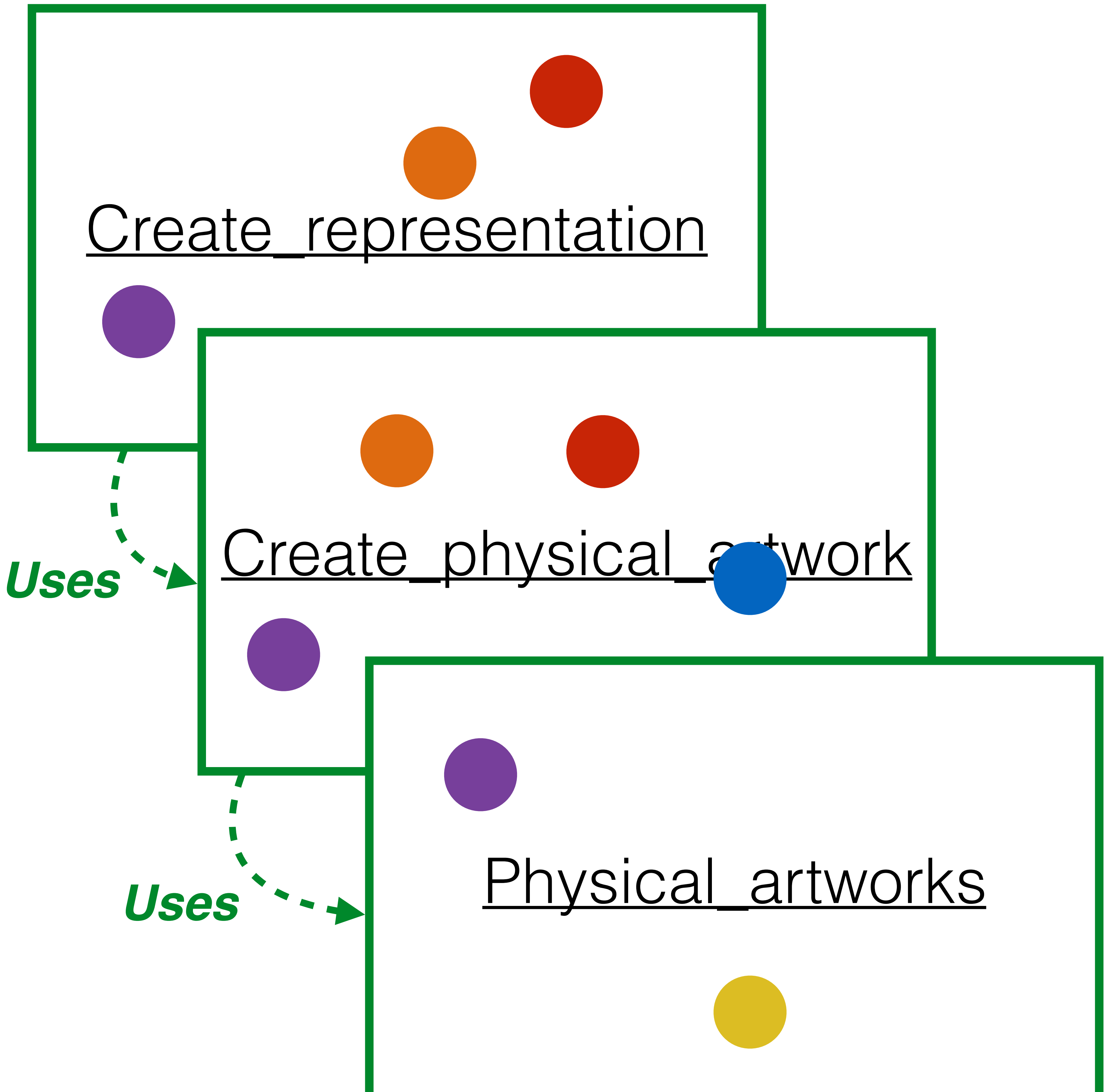
Create_physical_artwork

Physical_artworks

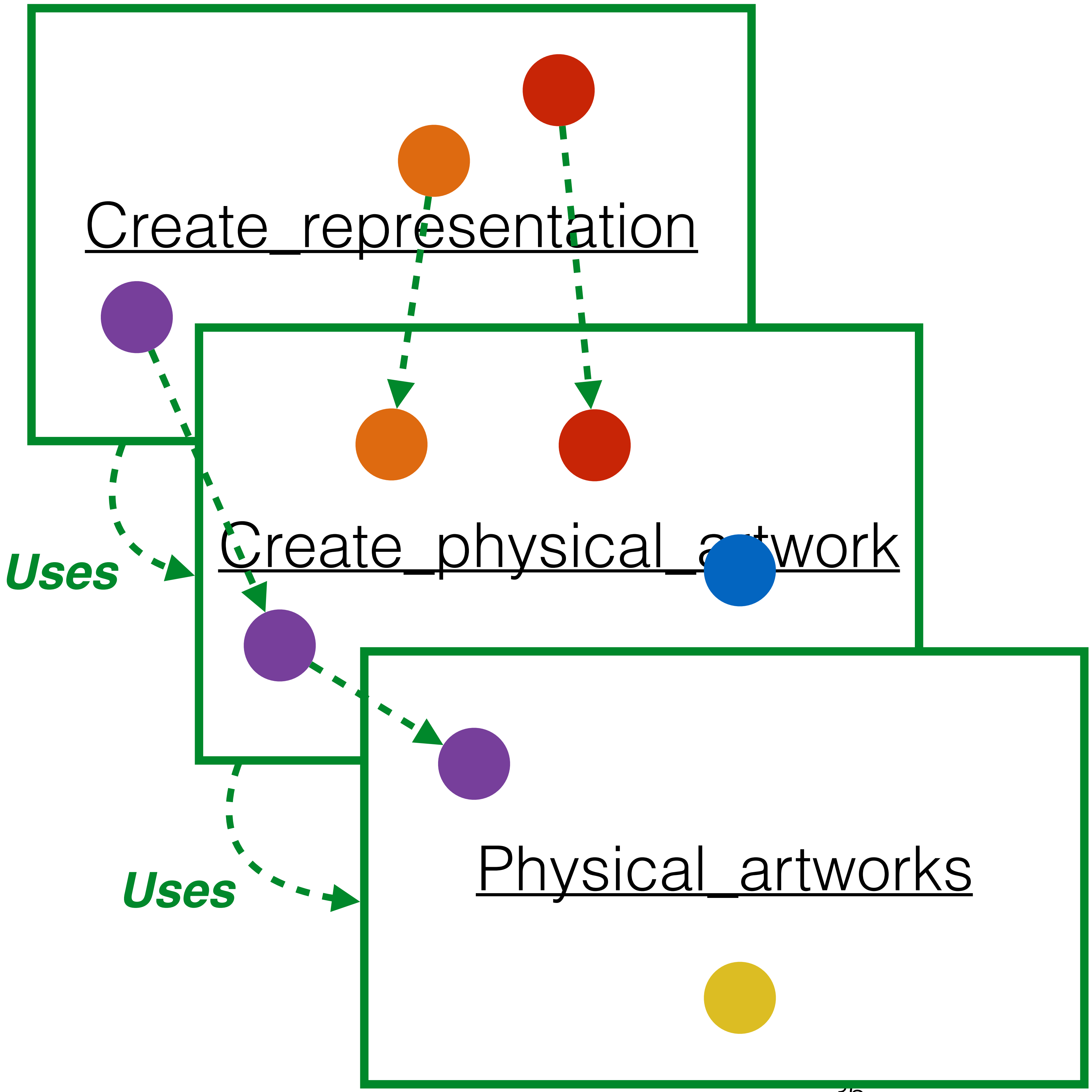
FrameNet


Create_representation
Uses
Create_physical_artwork
Uses
Physical_artworks

FrameNet


Create_representation
Create_physical_artwork
Physical_artworks
Uses
Uses

FrameNet


Create_representation
Create_physical_artwork
Uses
Physical_artworks
Uses

FrameNet

FrameNet: Lexicon

- ~1000 **frames** represent scenarios. Most are associated with **lexical units** (a.k.a. **predicates**). Berkeley FrameNet currently has 13k LUs (5k nouns, 5k verbs, 2k adjectives).

- **Frame elements** (a.k.a. **roles**) represent participants/components of those scenarios. **Core** vs. **non-core**.

- Frames and their corresponding roles are linked together in the lexicon.

- Frames are explained with textual descriptions.

Create_physical_artwork

Lexical Unit Index

Definition:

A Creator creates an artifact that is typically an iconic Representation of an actual or imagined entity or event. The Representation may also be evocative of an idea while not based on resemblance.

> Diagrams must be clearly DRAWN on construction paper. CNI
>
> I TOOK his picture and told him that if it came out well I would make him a copy.
>
> In about 1305 and 1306 Giotto PAINTED a notable series of 38 frescoes.

FEs:

Core:

Creator [cre]
Semantic Type: Sentient

An individual or individuals that bring the Representation into existence.

> Supposedly, the artist DREW the picture from memory.

Representation [rep]

The entity that is created to represent either iconically or abstractly.

> Most of us know where we TOOK a photo but have a harder time remembering the time we took it.

Non-Core:

Depictive [dep]

This FE describes the Creator as being in some state during the creation of the Representation.

Descriptor []

A characteristic of the Creator or the Representation.

Lexical Units:

artist.n, cast.v, draw.v, paint.v, sculpt.v, take_((picture)).v

Created by 605 on 11/21/2005 03:47:00 PST Mon

Lexical Unit	LU Status	Lexical Entry Report	Annotation Report	Annotator ID	Created Date
artist.n	**Created**	Lexical entry	Annotation	361	03/28/2007 03:10:10 PDT Wed
cast.v	**Created**	Lexical entry		597	06/09/2008 01:41:45 PDT Mon
draw.v	**Finished_Initial**	Lexical entry	Annotation	605	11/21/2005 05:28:34 PST Mon
paint.v	**Finished_Initial**	Lexical entry	Annotation	605	11/21/2005 05:26:23 PST Mon
sculpt.v	**Created**	Lexical entry		597	05/23/2008 02:55:21 PDT Fri
take_((picture)).v	**Created**	Lexical entry		605	11/21/2005 05:29:24 PST Mon

FrameNet Annotations

- Sheila and I had our **picture** **taken** by James.

FrameNet Annotations

- Sheila and I had our **picture** **taken** by James.

Create_physical_artwork

Creator

Representation

Physical_artworks

Creator

Artifact

Represented

FrameNet Annotations

- Sheila and I had our **picture** **taken** by James.

Create_physical_artwork

Creator	"James"
Representation	"our picture"

Physical_artworks

Creator

Artifact

Represented

FrameNet Annotations

- Sheila and I had our **picture** **taken** by James.

Create_physical_artwork

Creator "James"

Representation "our picture"

Physical_artworks

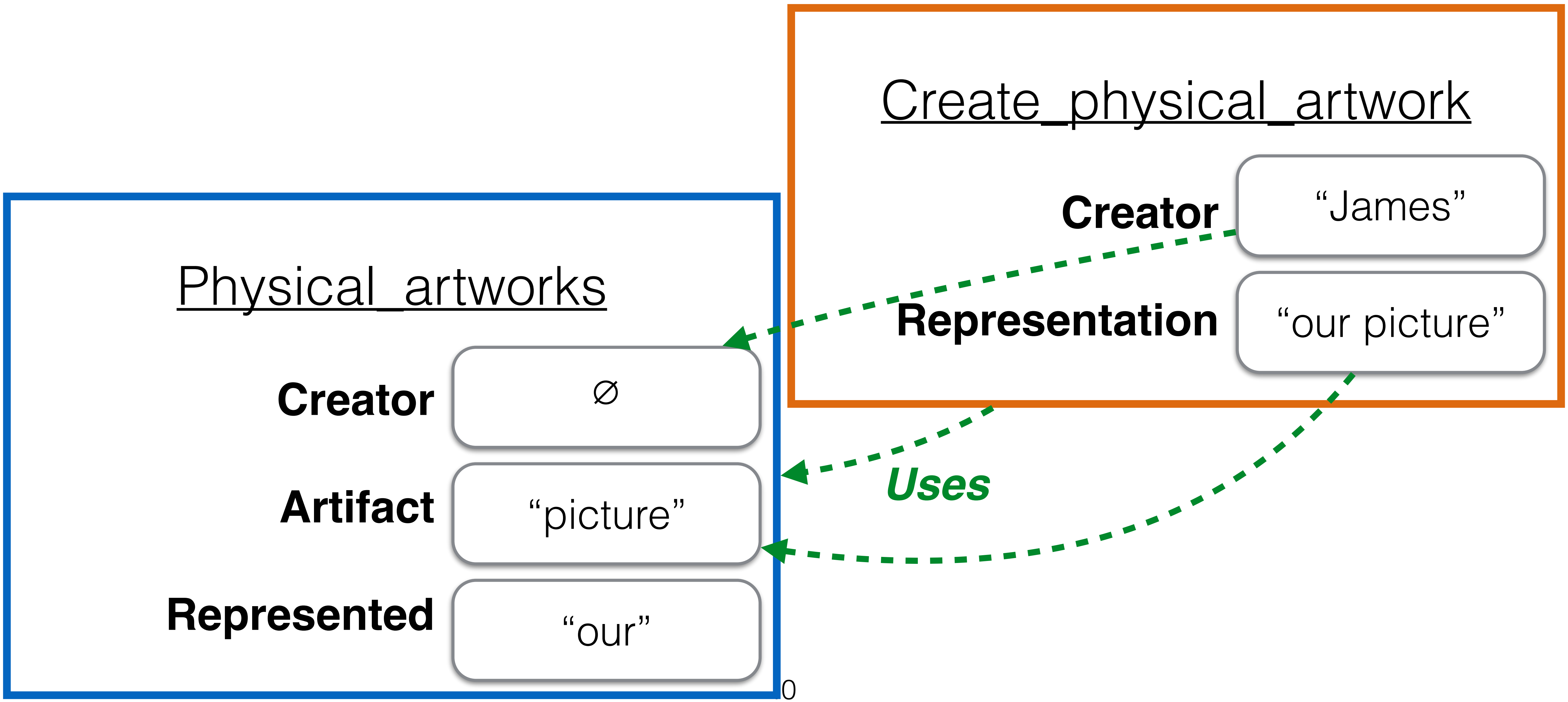
Creator ∅

Artifact "picture"

Represented "our"

FrameNet Annotations

- Sheila and I had our **picture** **taken** by James.



Languages with FrameNets

Languages with FrameNets

FrameNet Parsing

- SEMAFOR system from CMU has been applied to tasks as diverse as stock prediction and spoken dialogue segmentation

  http://www.ark.cs.cmu.edu/SEMAFOR/

  http://demo.ark.cs.cmu.edu/parse

- Ongoing research at CMU, Google, Edinburgh, …

SEMAFOR

- Open source system by Das et al. at CMU
- Pipeline similar (but not identical) to traditional SRL:

1. **Preprocessing:** run a dependency parser
2. **Target identification:** find the predicates
   heuristics/whitelist
3. **Frame identification:** classify the predicates into frames
   challenge: unseen predicates. semi-supervised methods

SEMAFOR

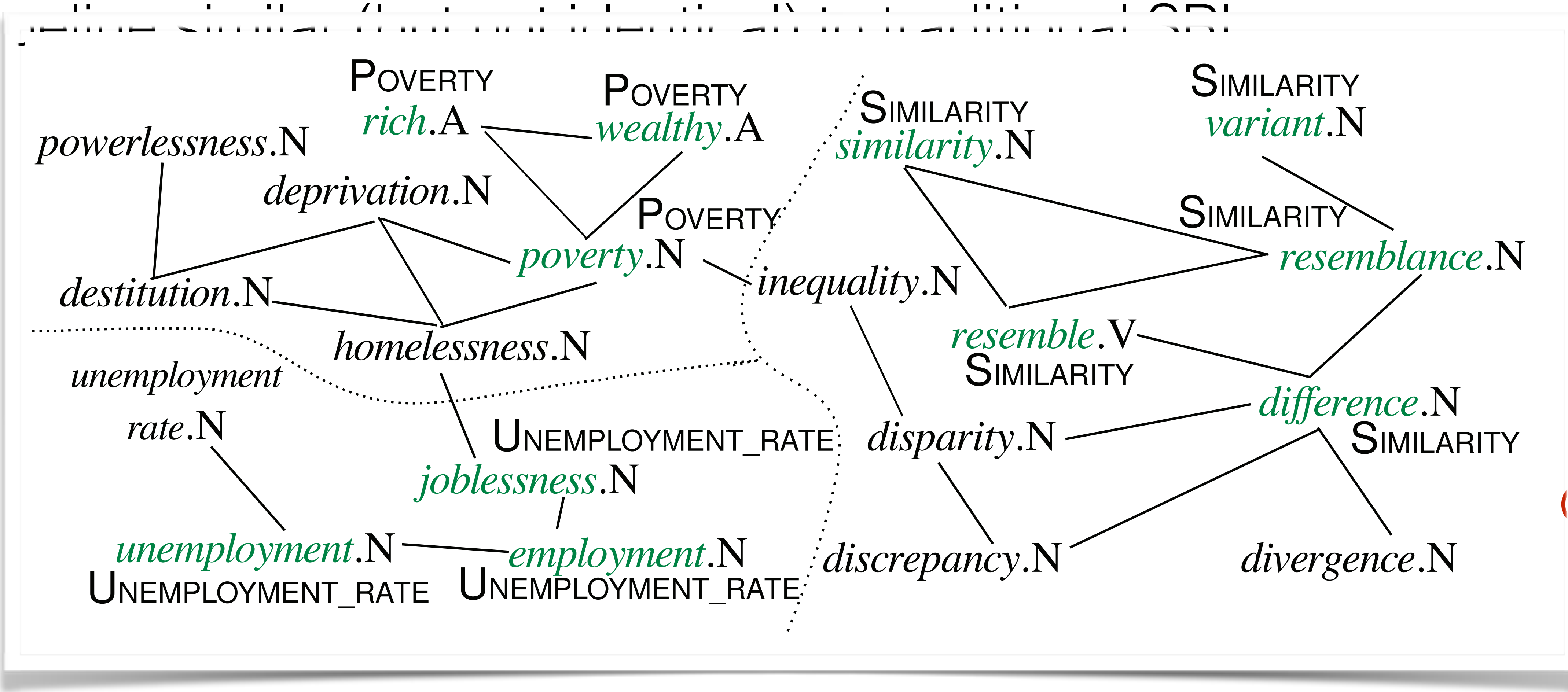
- Open source system by Das et al. at CMU
- Pi

1

2

3

ds



SEMAFOR

- Open source system by Das et al. at CMU

- Pipeline similar (but not identical) to traditional SRL:

1. **Preprocessing:** run a dependency parser

2. **Target identification:** find the predicates
   heuristics/whitelist
3. **Frame identification:** classify the predicates into frames
   challenge: unseen predicates. semi-supervised methods

SEMAFOR

- Open source system by Das et al. at CMU
- Pipeline similar (but not identical) to traditional SRL:
  1. **Preprocessing:** run a dependency parser
  2. **Target identification:** find the predicates
     heuristics/whitelist
  3. **Frame identification:** classify the predicates into frames
     challenge: unseen predicates. semi-supervised methods
  4. **Argument identification:** for each role evoked by the predicate, consider possible arguments in the sentence
     challenge: constraints between arguments.
- See Das et al. 2014 for details

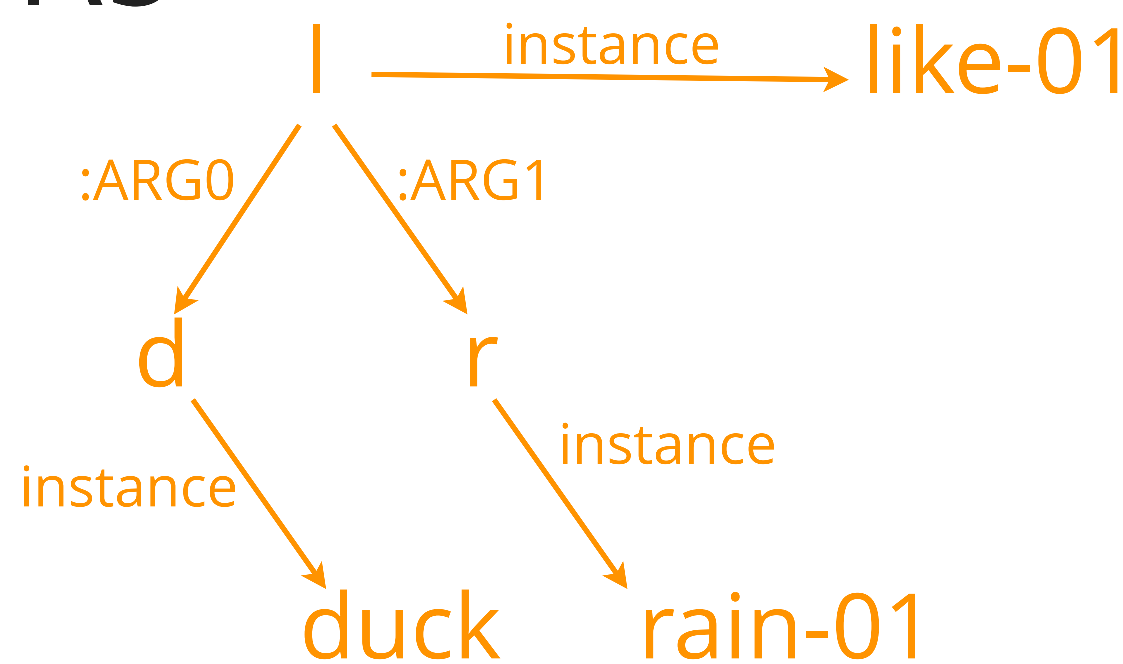
Abstract Meaning Representation

(Banarescu et al., LAW 2013)

A graph-based representation of lexical concepts and typed relations between those concepts that are denoted by an English sentence.

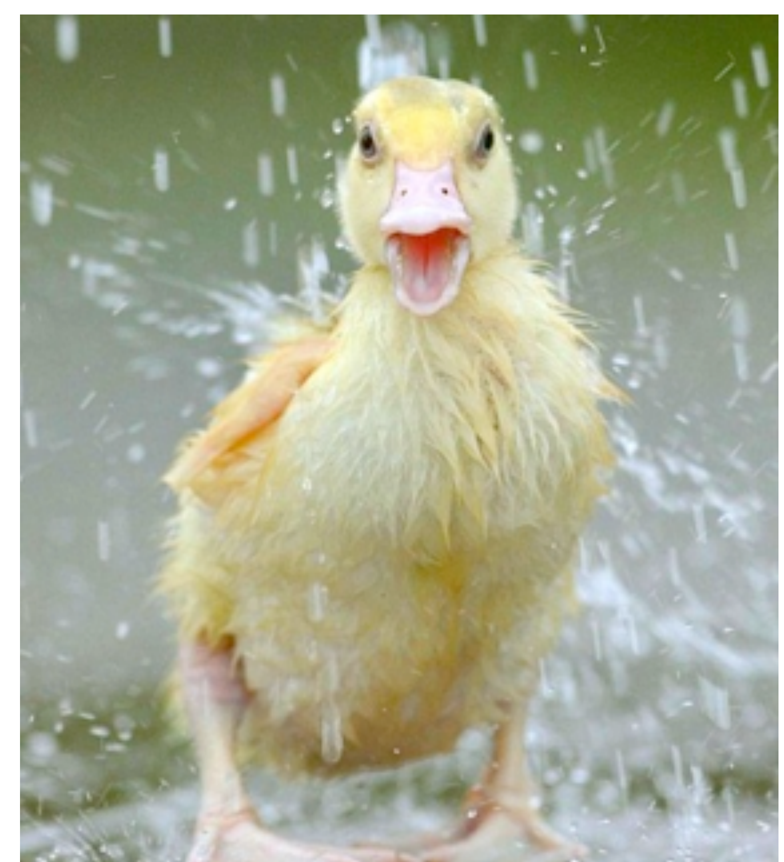
AMR integrates several aspects of lexical/relational meaning—abstracting away from the grammatical details—in a single structure designed to support rapid corpus annotation and data-driven NLP.

AMRs



(l / like-01
  :ARG0 (d / duck)
  :ARG1 (r / rain-01))

- ducks like rain
- the duck liked that it was raining

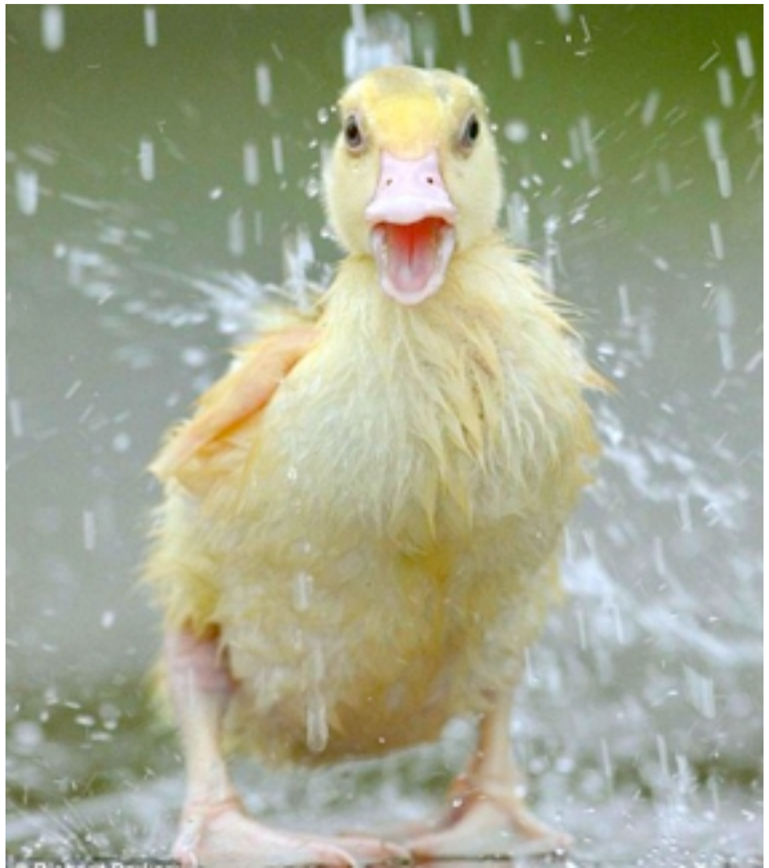


AMRs

```
(l / like-01
  :ARG0 (d / duck)
  :ARG1 (r / rain-01))
```

```
(s2 / see-01
   :ARG0 (i / i)
   :ARG1 (d / duck
         :poss (s / she)))
```

- I saw her duck



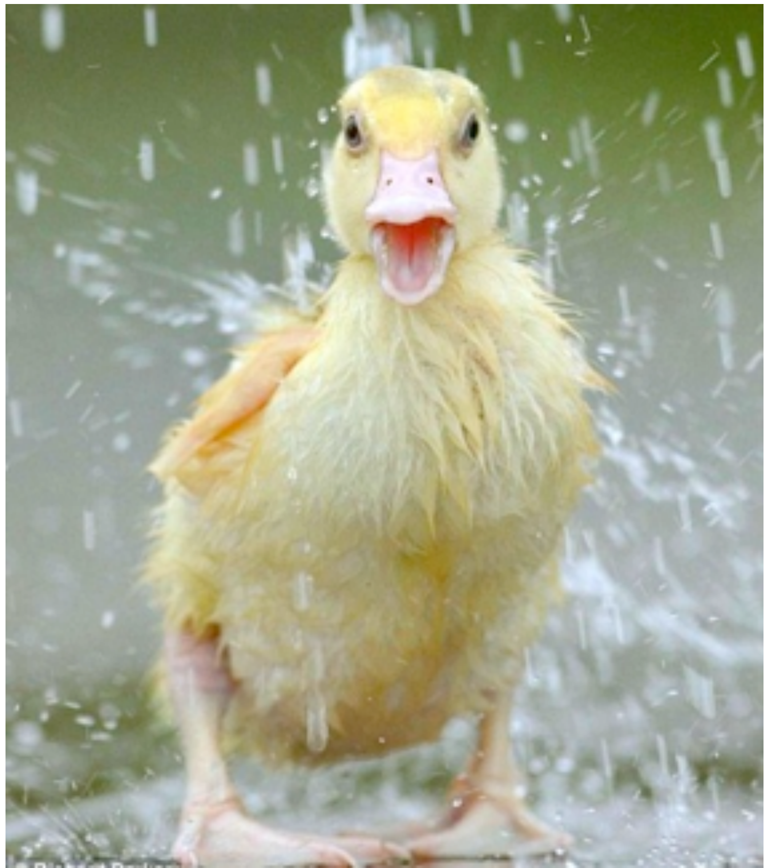
(l / like-01
  :ARG0 (d / duck)
  :ARG1 (r / rain-01))

AMRs

(s2 / see-01
  :ARG0 (i / i)
  :ARG1 (d / duck
    :poss (s / she)))

(s2 / see-01
  :ARG0 (i / i)
  :ARG1 (d / duck-01
    :ARG0 (s / she)))

- I saw her duck (alternate interpretation)



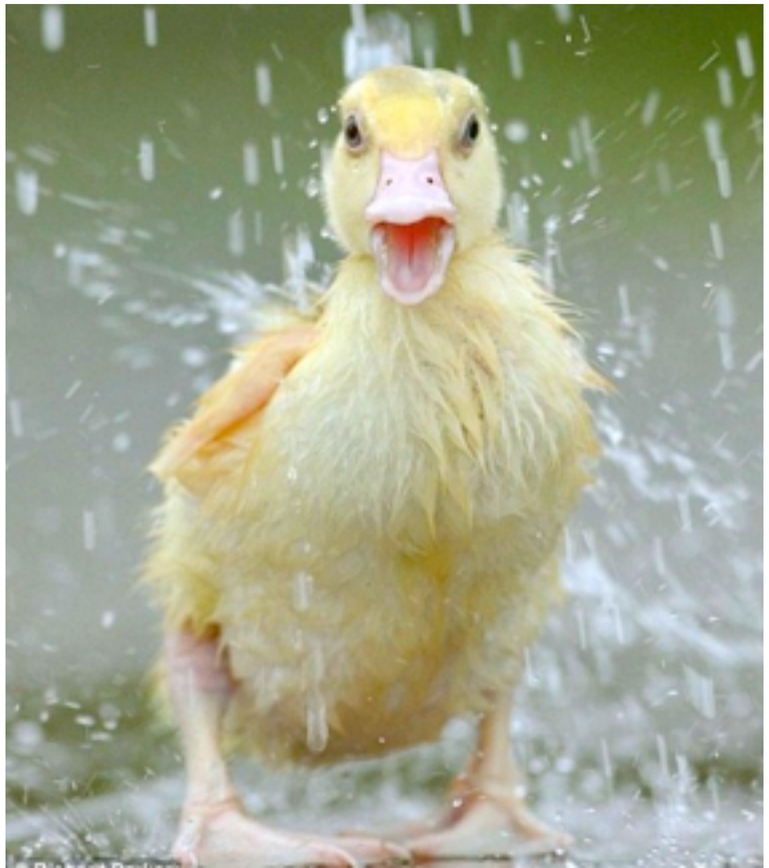
AMRs

```
(l / like-01
  :ARG0 (d / duck)
  :ARG1 (r / rain-01))
```

```
(s2 / see-01
   :ARG0 (i / i)
   :ARG1 (d / duck
           :poss (s / she)))
```

```
(s2 / see-01
   :ARG0 (s / she)
   :ARG1 (d / duck
           :poss s))
```

- She saw her (own) duck

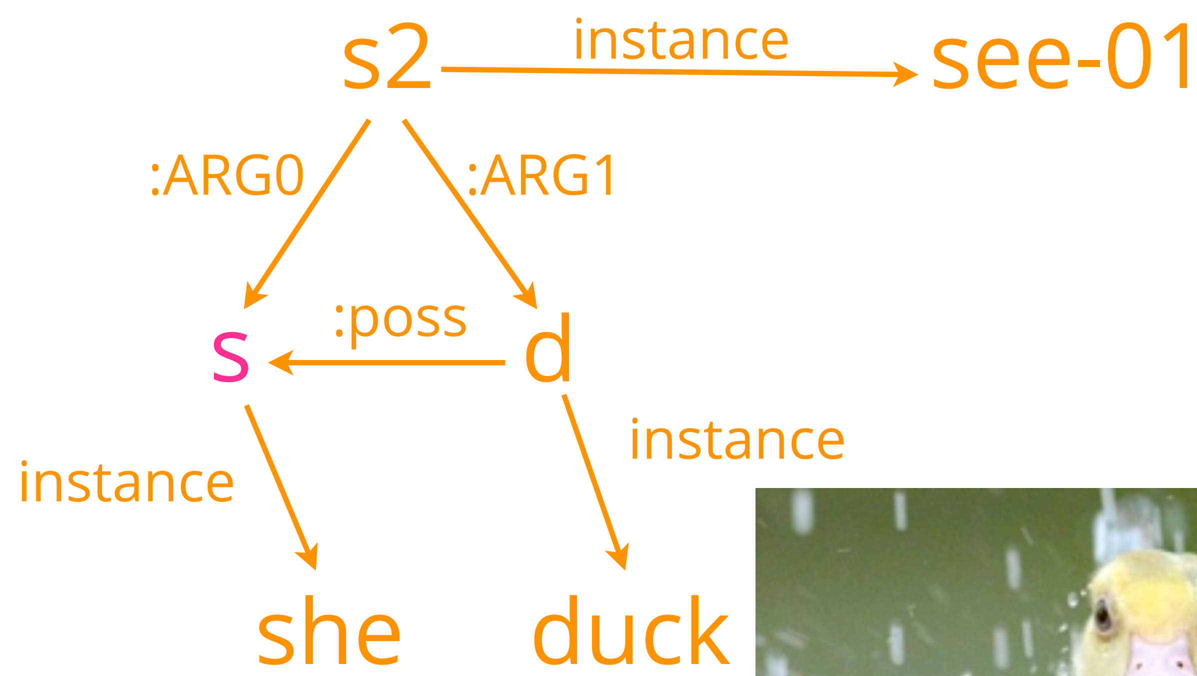


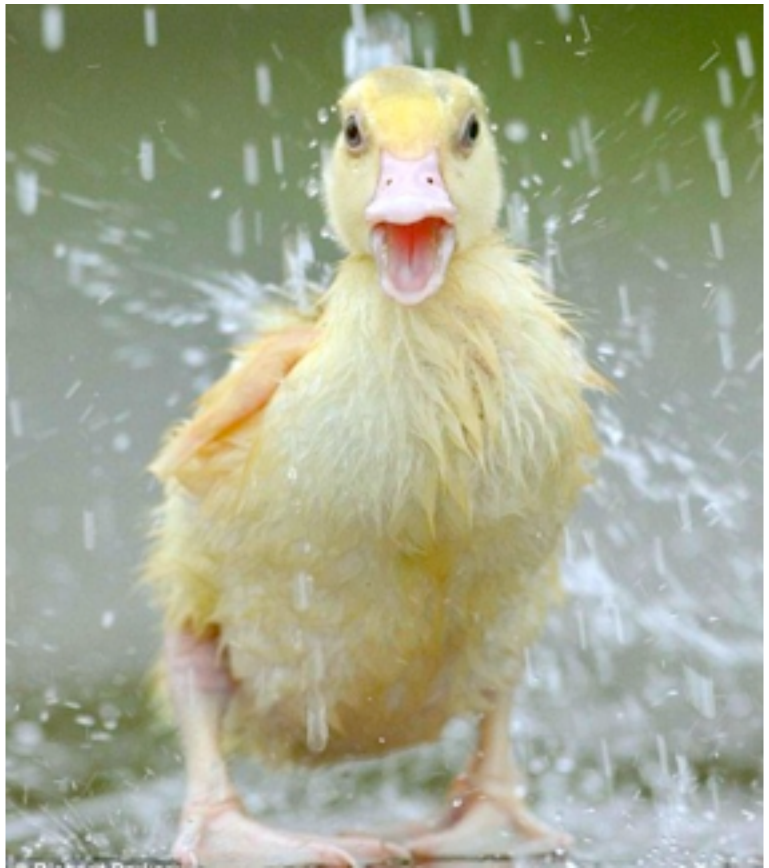
AMRs

```
(l / like-01
  :ARG0 (d / duck)
  :ARG1 (r / rain-01))
```

```
(s2 / see-01
   :ARG0 (i / i)
   :ARG1 (d / duck
           :poss (s / she)))
```

```
(s2 / see-01
   :ARG0 (s / she)
   :ARG1 (d / duck
           :poss s))
```





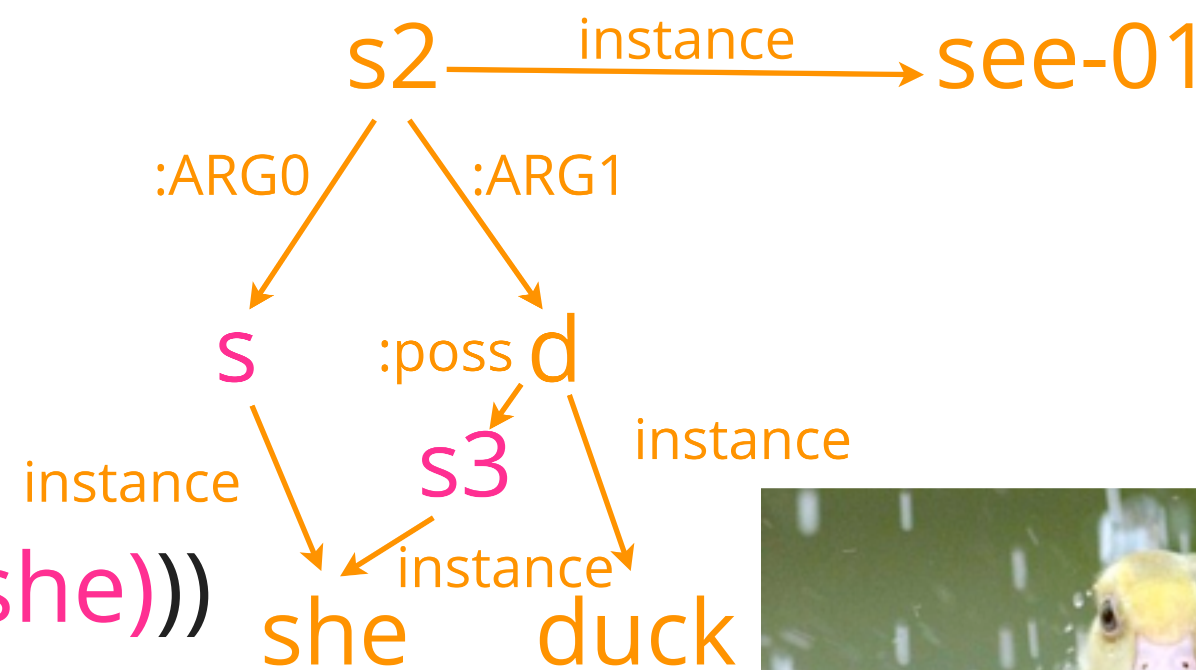
- She saw her (own) duck

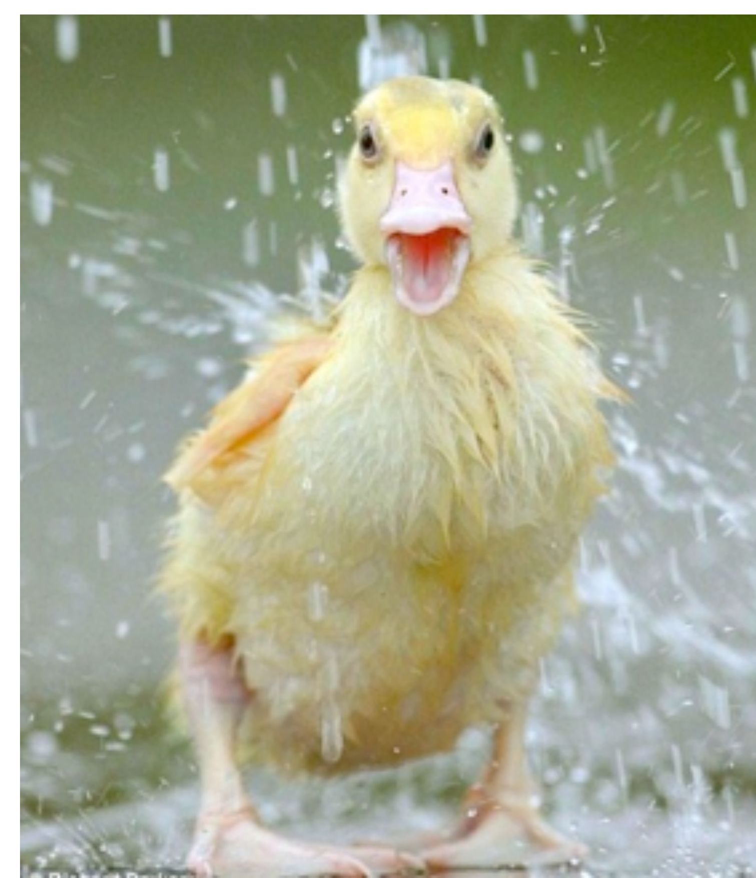
AMRs

(l / like-01
:ARG0 (d / duck)
:ARG1 (r / rain-01))

(s2 / see-01
:ARG0 (i / i)
:ARG1 (d / duck
:poss (s / she)))

(s2 / see-01
:ARG0 (s / she)
:ARG1 (d / duck
:poss (s3 / she)))





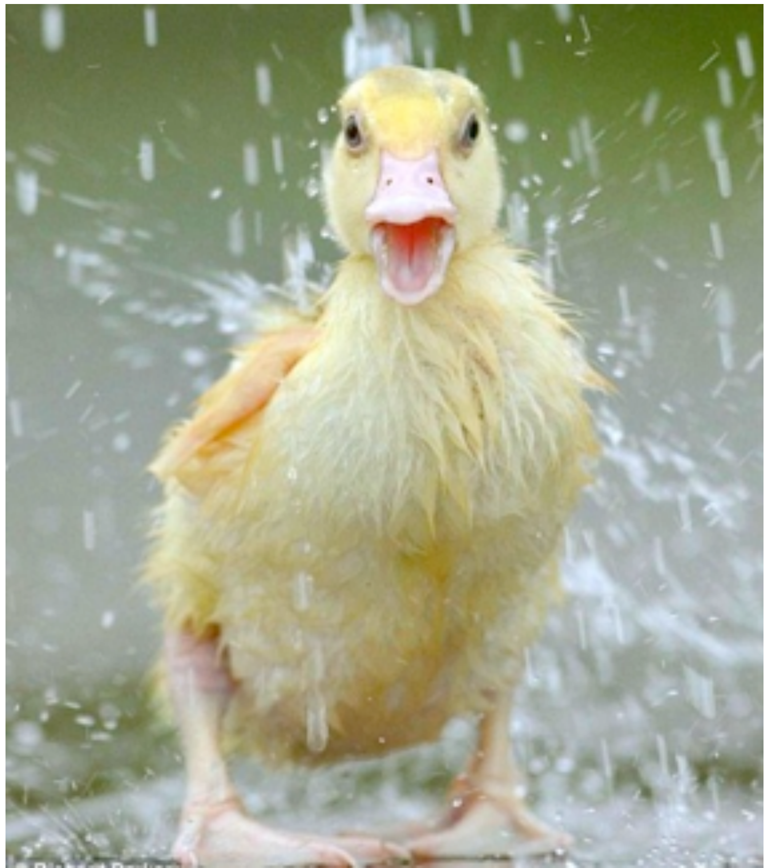
- She saw her (someone else's) duck

AMRs

(l / like-01
  :ARG0 (d / duck)
  :ARG1 (r / rain-01))

(h / happy
    :domain (d / duck
            :ARG0-of (l / like-01
                    :ARG1 (r / rain-01))))

- Ducks who like rain are happy

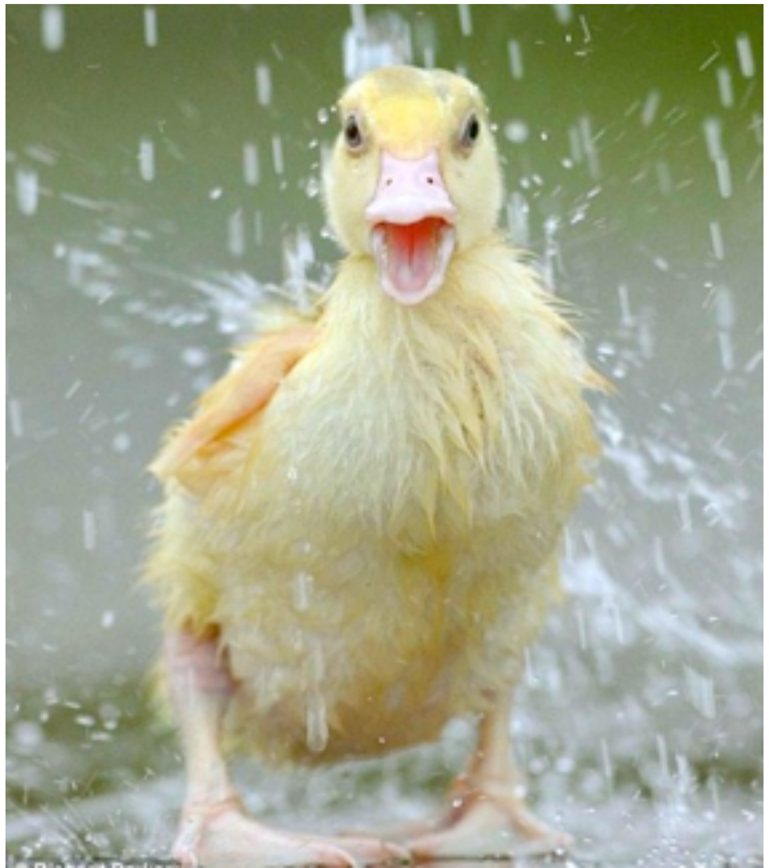


AMRs

```
(l / like-01
  :ARG0 (d / duck)
  :ARG1 (r / rain-01))
```

```
(h / happy
   :domain (d / duck
             :ARG0-of (l / like-01
                         :ARG1 (r / rain-01))))
```

- Ducks who like rain are happy



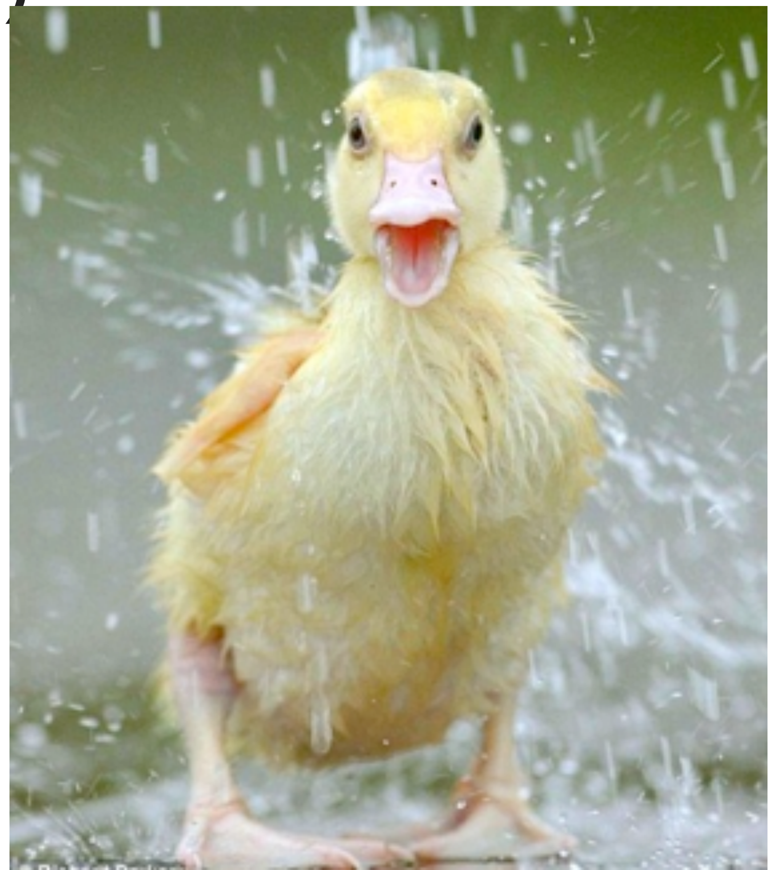
AMRs

```
(l / like-01
  :ARG0 (d / duck)
  :ARG1 (r / rain-01))
```

```
(h / happy
  :domain (d / duck
            :ARG0-of (l / like-01
                       :ARG1 (r / rain-01))))
```

```
(l / like-01
  :ARG0 (d / duck
          :domain-of/:mod (h / happy))
  :ARG1 (r / rain-01))
```

- Happy ducks like rain



Police release security footage of the man they believe assaulted a 12-year-old in her home.

```
(r / release-01
    :ARG0 (p / police)
    :ARG1 (f / footage
        :mod (s / security)
        :topic (m / man
            :ARG0-of (a / assault-01
                :ARG1 (g / girl
                    :age (t / temporal-quantity :quant 12
                        :unit (y / year)))
                :ARG1-of (b / believe-01
                    :ARG0 p)
                :location (h / home
                    :poss g)))))
```

Police release security footage of the man they believe assaulted a 12-year-old in her home.

```
(r / release-01
    :ARG0 (p / police)
    :ARG1 (f / footage
        :mod (s / security)
        :topic (m / man
            :ARG0-of (a / assault-01
                :ARG1 (g / girl
                    :age (t / temporal-quantity :quant 12
                        :unit (y / year)))
                :ARG1-of (b / believe-01
                    :ARG0 p)
                :location (h / home
                    :poss g)))))
```

AMR Features

- PropBank predicate-argument semantics
- name & value entities; entity linking (wikification)
- coreference
- modality, negation, questions
- relations between nominals
- canonicalization of content words (remove inflectional morphology, convert adv → adj → noun → verb where possible)

his trial → (t / try-02 :ARG1 (h / he))

AMR Features

- PropBank predicate-argument semantics
- name & value entities; entity linking (wikification)
- coreference
- modality, negation, questions
- relations between nominals

history teacher → (p / person
:ARG0-of (t / teach-01
:ARG1 (h / history)))

- canonicalization of content words (remove inflectional morphology, convert adv → adj → noun → verb where possible)

his trial → (t / try-02 :ARG1 (h / he))

AMR Assets

- Snazzy annotation tool
- Evaluation method (smatch)
- Extensive documentation (guidelines, help pages in tool, heuristics in tool)
- Tutorial: https://github.com/nschneid/amr-tutorial
- Close coordination with PropBank
- Annotation sites: CU, ISI, SDL, LDC
- Data: ~40,000 AMRs released (as of 2016)

Abstract Meaning Representation (AMR)

(Banarescu et al., LAW 2013)

A graph-based representation of lexical concepts and typed relations between those concepts that are denoted by an English sentence.

AMR integrates several aspects of lexical/relational meaning—abstracting away from the grammatical details—in a single structure designed to support rapid corpus annotation and data-driven NLP.

Abstract Meaning Representation (AMR)

(Banarescu et al., LAW 2013)

A graph-based representation of lexical concepts and typed relations between those concepts that are denoted by an English sentence.

AMR integrates several aspects of lexical/relational meaning—abstracting away from the grammatical details—in a single structure designed to support rapid corpus annotation and data-driven NLP.

(Flanigan et al., ACL 2014)

AMR Parsing: JAMR

- Open source system from CMU
- Pipeline:
  1. **Preprocessing:** dependency parsing, NER
  2. **Concept identification:** map word sequences to graph fragments
  3. **Relation identification:** connect the fragments into a rooted DAG (novel MSCG algorithm)
- See Flanigan et al. 2014 for details

assaulted a **12-year-old**

assaulted a **12-year-old**

(a / assault-01)

assaulted a **12-year-old**

(a / assault-01)

```
(g / girl
   :age (t / temporal-quantity :quant 12
           :unit (y / year)))
```

assaulted a **12-year-old**

(a / assault-01)

ARG1

(g / girl
:age (t / temporal-quantity :quant 12
:unit (y / year)))

assaulted a **12-year-old**

```
(a / assault-01
    :ARG1 (g / girl
              :age (t / temporal-quantity :quant 12
                        :unit (y / year))))
```

Summary

- For verbs (and other semantic predicates), there are complicated patterns of **argument structure**—how semantic **arguments/roles** correspond to syntactic slots.
- Lexicons formalize this in different ways: **PropBank**, **VerbNet**, **FrameNet**
  - Corpora annotated according to each of these lexicons for training **semantic role labelers**.
  - **FrameNet** is the richest theory (deep frames), but that imposes practical limits on the size of the lexicon and annotated corpora.
  - **PropBank** has good coverage of English verbs, and large amount of annotated corpora (WSJ + more!). But a bit superficial (verb-specific frames).
- PropBank event predicates are used in **AMR**, a meaning representation that also captures named entities, negation/modality, coreference, and other aspects of semantics in a graph for each sentence.