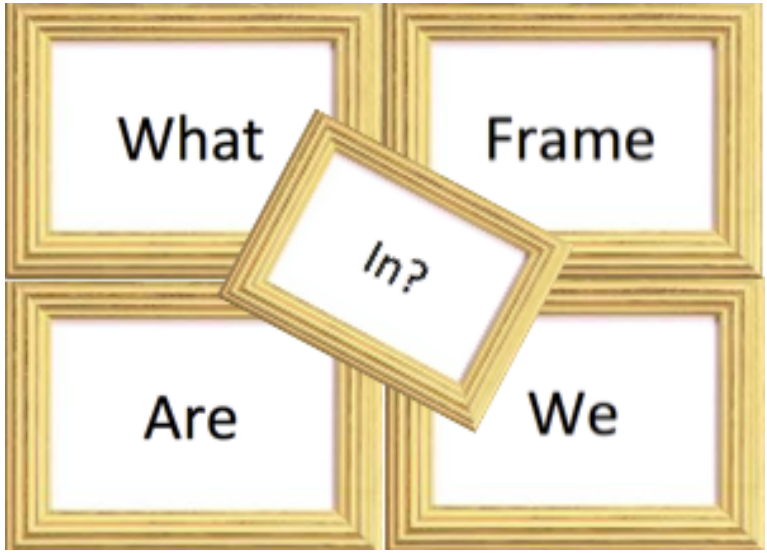

Frame Semantics

Tatiana Anikina

Seminar: Hot and Odd Topics in Semantics

Saarland University
04.06.2018

Outline

- Frame as a Linguistic Concept
- Historical Background
- Use Cases for NLP
- Frame Identification
- Semantic Role Labeling
- Open Issues

Let’s answer following questions:

What are the frames? When do we need them?

How to find frames in a sentence?

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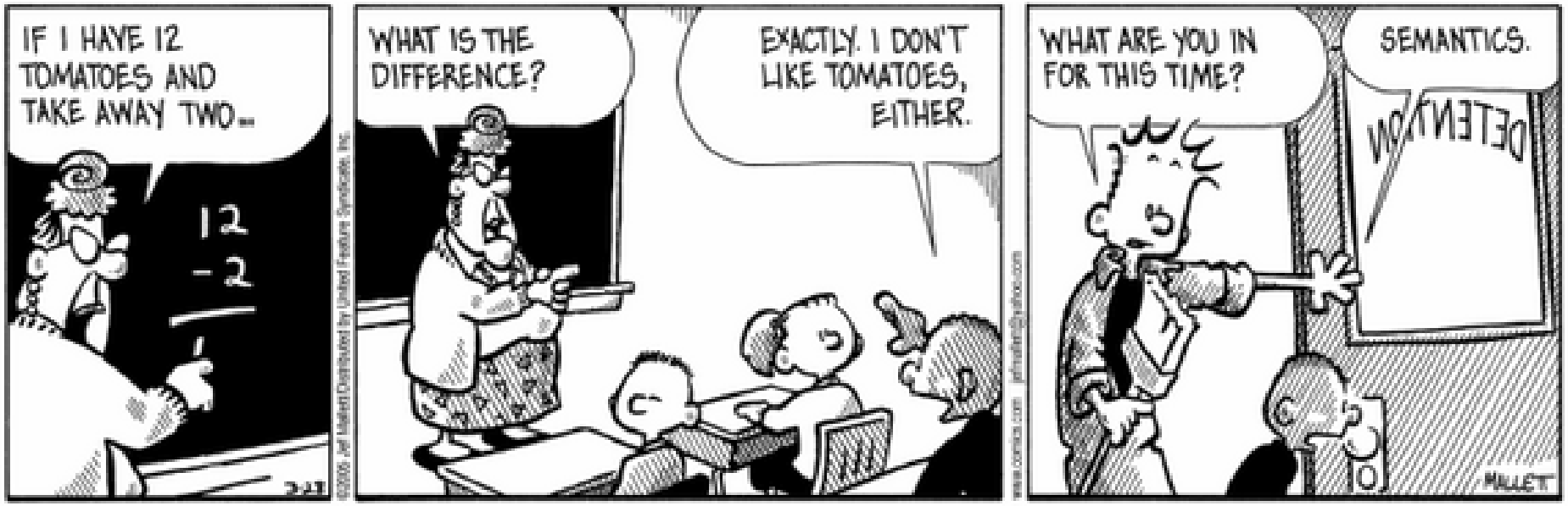
Frame Mismatch



Frame as a Linguistic Concept

Charles Fillmore (1977a):

Meanings are relativized to scenes.

Frames define how we **interpret our environment**, formulate & understand messages, create internal model of the world.

Language has not only grammar rules and lexicon items, it also has frames!

Frame as a Linguistic Concept

Particular words or speech formulas, grammatical choices are associated in memory with particular frames.

Interactional Frames: appropriate contexts of interaction (e.g. greeting frame).

Cognitive/conceptual frames: setting+protagonists+objects (e.g. buying event).

Frame as a Linguistic Concept

Our experiences are memorable because we have some **cognitive frames/schemes** for their interpretation.

E.g.: **grapefruit vs orange**

For 7-years-old children orange is an object which can be peeled and eaten piece by piece.

Grapefruit is an object which can be cut in half and eaten using a spoon.

Frame as a Linguistic Concept

Breakfast frame:

The first meal in the day after one wakes up.

Can differ a lot depending on country/age/personal preferences.

E.g.: Breakfast in Russia vs Breakfast in Japan

Frame as a Linguistic Concept

Breakfast frame:

The first meal in the day after one wakes up.

Can differ a lot depending on country/age/personal preferences.

Frame as a Linguistic Concept

Lexical frames are not easy to define:

Good + chair/steak/teacher ok!

Good + leaf/triangle/widow ???

Money frame: a medium used for exchanging goods and services.

Money = prize, change, ransom, tip, bribe...

The goal of frame semantics is to create **a uniform representation** for word/sentence meanings and text interpretations.

Snow Frame Example ;-)

Frame as a Linguistic Concept

Frames **introduce situations (events)** together with corresponding properties, participants and their roles.

Frames provide an **outline of the event** and define a set of **plausible questions** (e.g. what/where/how).

Not all possible slots must be filled, some of them are optional.

E.g.: Sam bought new shoes.

Where did he buy the shoes? Why did he buy them?

How expensive were the new shoes? ...

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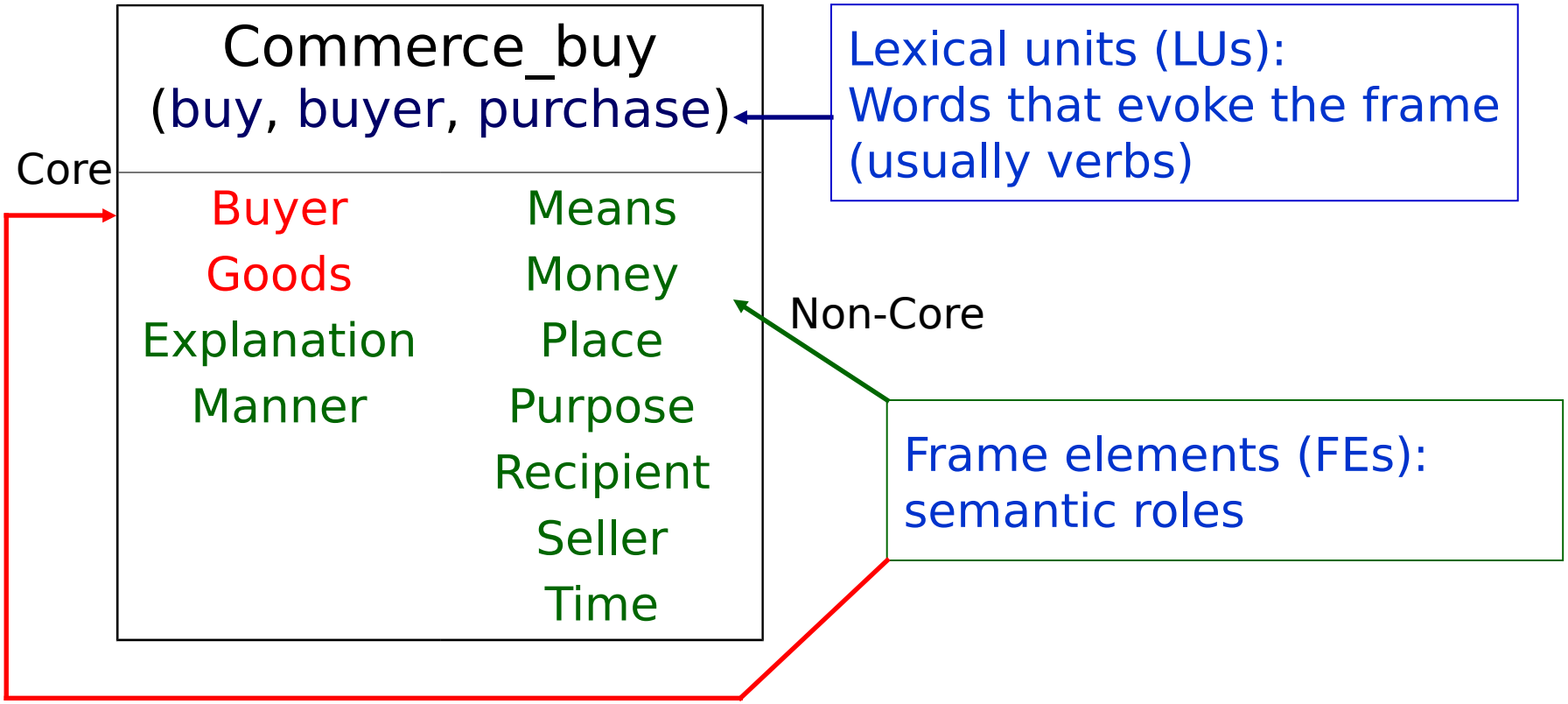


[$_{\text{Agent}}$ *Sam*] ***bought*** [$_{\text{Goods}}$ *new shoes*] [$_{\text{Place}}$ *in Karstadt*] [$_{\text{Time}}$ *yesterday*].

Historical Background: FrameNet

FrameNet is a large corpus of sentences annotated with frames. It was created in the late 90s.

FrameNet uses real language data from British National Corpus (BNC) and North American Newswire (NAN) corpora.

FrameNet contains:

8900 lexical units

625 frames

135000 sentences

Historical Background: FrameNet

Frame Index

A B C D E F G H I J K L M N
O P Q R S T U V W X Y Z

Abandonment
Abounding_with
Absorb_heat
Abundance
Abusing
Access_scenario
Accompaniment
Accomplishment
Accoutrements
Accuracy
Achieving_first
Active_substance
Activity
Activity_abandoned_state
Activity_done_state
Activity_finish
Activity_ongoing
Activity_pause
Activity_paused_state
Activity_prepare
Activity_ready_state
Activity_resume
Activity_start
Activity_stop

Commerce_buy

Lexical Unit Index

Definition:

These are words describing a basic commercial transaction involving a Buyer and a Seller exchanging Money and Goods, taking the perspective of the Buyer. The words vary individually in the patterns of frame element realization they allow. For example, the typical pattern for the verb BUY: Buyer buys Goods from Seller for Money.

Abby bought a car from Robin for $5,000.

FEs:

Core:

Buyer [Byr]	The Buyer wants the Goods and offers Money to a Seller in exchange for them. Jess BOUGHT a coat. Lee BOUGHT a textbook from Abby.
Goods [Gds]	The FE Goods is anything (including labor or time, for example) which is exchanged for Money in a transaction. Only one winner PURCHASED the paintings

Historical Background: PropBank

PropBank is based on Penn TreeBank and is a data-driven resource.

PropBank is focused on verb annotation and has no abstraction beyond verb senses.

Argument roles are not frame-specific.

PropBank contains:

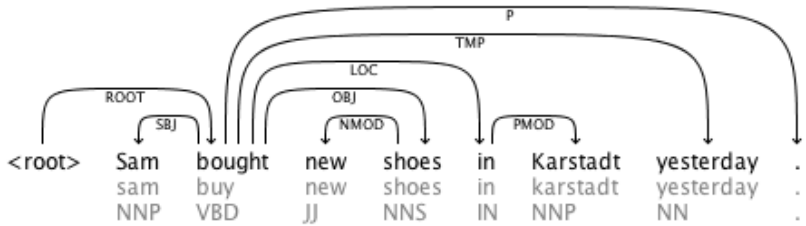
3324 frame files

113000 propositions

Historical Background: PropBank

	Sam	bought	new	shoes	in	Karstadt	yesterday	.
buy.01	A0		A1		AM-LOC		AM-TMP	

Parsing sentence required 10ms.



Core arguments:
A0 – Agent, A1 – Patient or Theme
Non-core arguments:
AM-LOC, TMP, CAU, DIR, NEG etc.

ID	Form	Lemma	PLemma	POS	PPOS	Feats	PFeats	Head	PHead	Deprel	PDeprel	IsPred	Pred	Args: buy.01
1	Sam	_	sam	_	NNP	_	_	_	2	_	SBJ	_	_	A0
2	bought	_	buy	_	VBD	_	_	_	0	_	ROOT	Y	buy.01	_
3	new	_	new	_	JJ	_	_	_	4	_	NMOD	_	_	_
4	shoes	_	shoes	_	NNS	_	_	_	2	_	OBJ	_	_	A1
5	in	_	in	_	IN	_	_	_	2	_	LOC	_	_	AM-LOC
6	Karstadt	_	karstadt	_	NNP	_	_	_	5	_	PMOD	_	_	_
7	yesterday	_	yesterday	_	NN	_	_	_	2	_	TMP	_	_	AM-TMP
8	.	_	.	_	.	_	_	_	2	_	P	_	_	_

Use Cases for NLP

Frames helps to capture “intermediate semantics”.

Some words **evoke frames** (e.g. *buy* → *commerce*) which have arguments with specific roles (*buyer*, *goods*).

Frames are useful if we want to find the descriptions of the **same event** expressed with a different syntactic structure and using other words.

Use Cases:

Machine Translation, Q&A, Dialogue Systems

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Use Cases:

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Use Cases for NLP: Machine Translation

Create **lexical entries** for nouns, verbs, adjectives in language X that correspond to **FrameNet entries**.

Link parallel lexicon fragments by **common semantic frames**.

Parallel lexicon fragments provide valuable information about **different syntactic realizations** of frame semantics across different languages.

[$_{\text{Theme}}$ Dieses Buch] hat [$_{\text{Donor}}$ Anna] [$_{\text{Recipient}}$ mir] **geschenkt**.

[$_{\text{Donor}}$ Anna] **presented** [$_{\text{Recipient}}$ me] with [$_{\text{Theme}}$ this book].

Use Cases for NLP: Q&A

Answer extraction benefits from semantic role annotations.

Predicates with **similar semantics evoke the same frame** and share the same roles.

FrameNet provides **lists of surface realizations** for semantic roles and annotated sample sentences.

Q: What [$_{\text{Time}}$ year] did [$_{\text{Buyer}}$ the U.S.] **buy** [$_{\text{Goods}}$ Alaska]?

A: [$_{\text{Seller}}$ Russia] **sold** [$_{\text{Goods}}$ Alaska] to [$_{\text{Buyer}}$ the U.S.] in [$_{\text{Time}}$ 1867].

QA system can use the fact that the U.S. has the same role *buyer* in both sentences.

Use Cases for NLP: Dialogue Systems

Dialogue act recognition can incorporate syntactic and semantic relations between words using frames and semantic role labeling.

Can [$_{\text{Agent}}$ you] **put** [$_{\text{Theme}}$ a picture] [$_{\text{Goal}}$ on the wall]?

<predicate: put-3.1>

<agent: you>

<theme: posters or pictures>

<destination: on the wall>

Frame Identification

Task: relate predicates to the frames which they evoke.

Distributed Frame Identification [Hermann, 2014]:

Model takes **word embeddings** as an input and learns to identify semantic frames.

Word embeddings represent the **syntactic context of a predicate**.

The goal is to learn a matrix which maps high dimensional sparse representation into a lower dimensional space. The model learns **embeddings for all possible frames** and assigns the nearest frame label.

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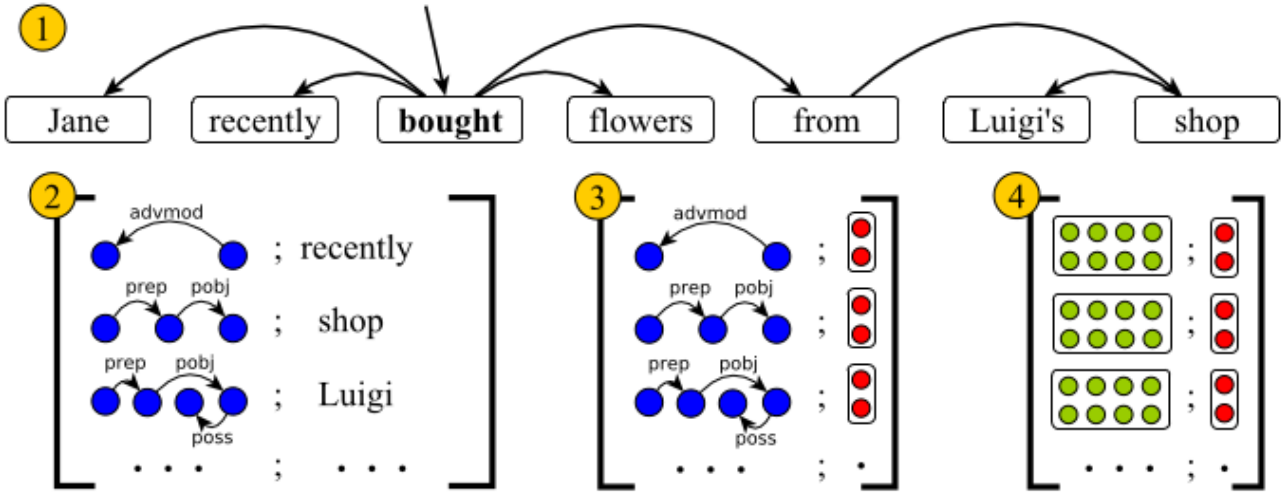
Frame Identification

Distributed Frame Identification:

Given a **dependency parse** (1) the model extracts all words matching **paths from the predicate** to its direct dependents (2).

Then model computes a **distributed vector representations** for words (3) and embedding vectors for each word are concatenated.

After that **the linear transformation function** is learned and parametrized by the context blocks (4).



Semantic Role Labeling

Task: find semantic roles for each argument of every predicate in a sentence.

Basic Algorithm (in a supervised fashion):

1. Prune unlikely constituents.
2. Use binary classification for remaining candidates (arg vs non-arg).
3. Assign possible semantic roles.
4. Re-rank (multiple labels for constituents).
5. Find best global label (semantic role for arg).

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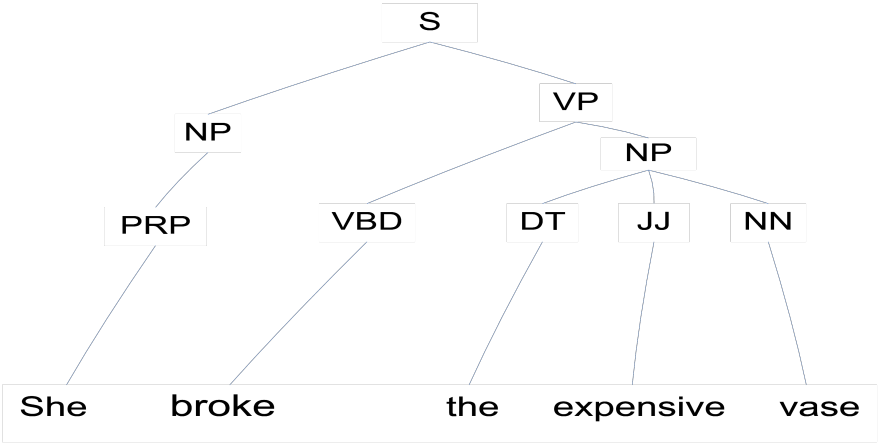
Semantic Role Labeling

Baseline features
[Gildea & Jurafsky, 2002]

Constituent Independent
- Target predicate (lemma)
- Voice
- Subcategorization

Constituent Specific
- Path
- Position (*left, right*)
- Phrase Type
- Governing Category (*S* or *VP*)
- Head Word



Target	*broke*
Voice	*active*
Subcategorization	*VP→VBD NP*
Path	*VBD↑VP↑S↓NP*
Position	*left*
Phrase Type	*NP*
Gov Cat	*S*
Head Word	*She*

Semantic Role Labeling: advanced

Neural Semantic Role Labeling with Dependency Path Embeddings

[Roth et al., 2016]

Motivation: sparse lexico-syntactic features in the training data (control & raising verbs, nested conjunctions etc.)

Approach: LSTM to model semantic relationships between the predicate and its arguments.

Path embeddings = vector representations of dependency paths

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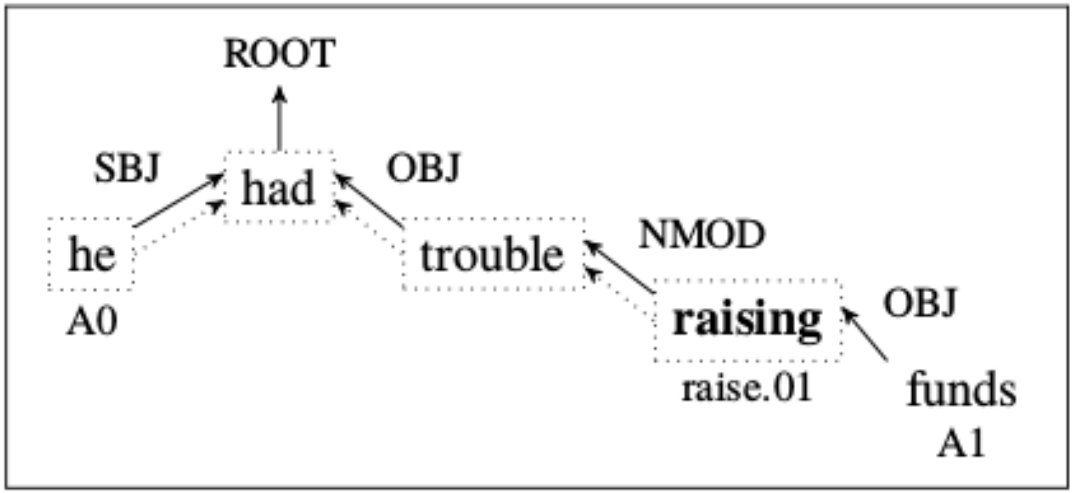
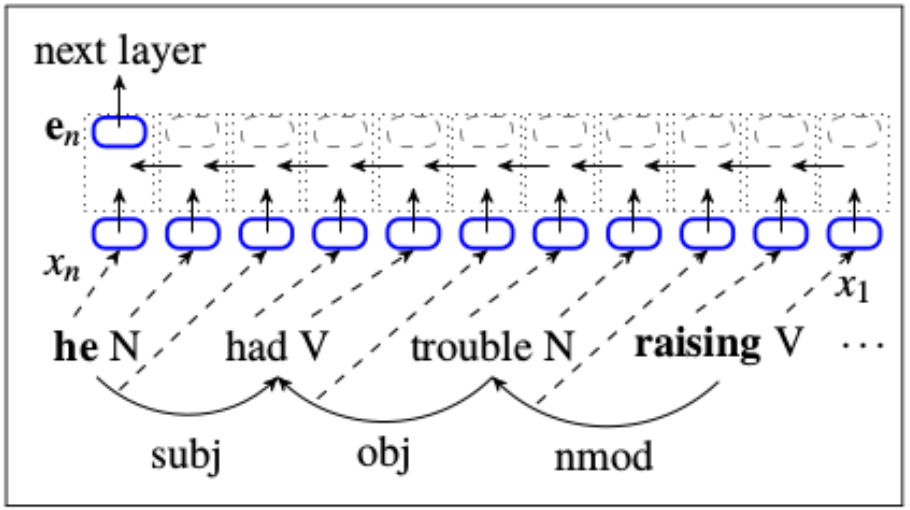
Semantic Role Labeling: advanced

Encoding dependencies as embeddings

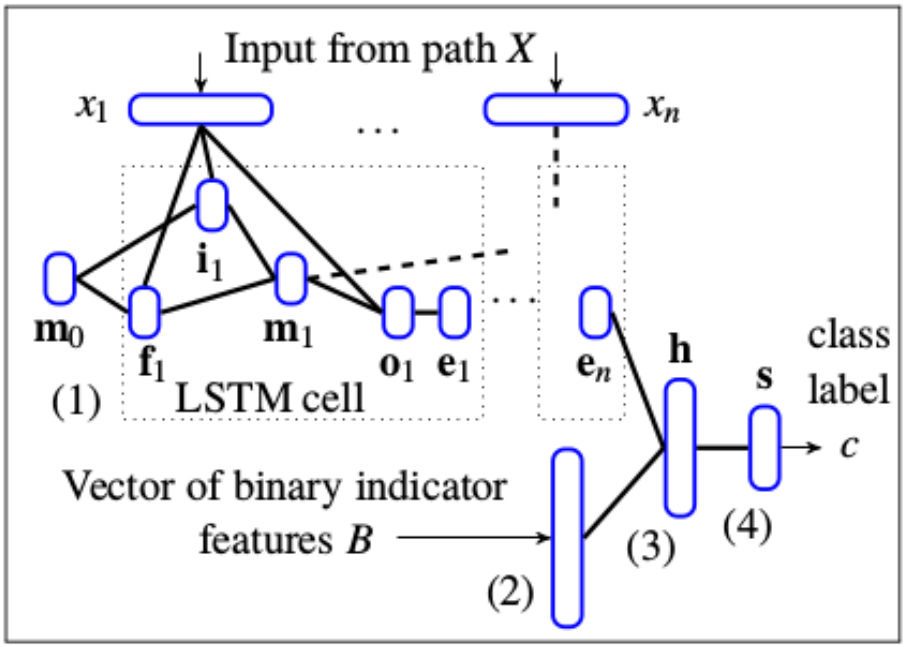


Dependency path between predicate *raising* and argument *he.*



Embedding computation for the path from *raising* to *he*.

Semantic Role Labeling: advanced



Joint learning of path embeddings + binary features:

1. The path sequence is fed into a LSTM layer.
2. Hidden layer h combines embedding e and binary input features B.
3. Output layer s assigns the highest probable class label c.

Semantic Role Labeling: advanced

Results:

System (local, single)	P	R	F_1
Björkelund et al. (2010)	87.1	84.5	85.8
Lei et al. (2015)	–	–	86.6
FitzGerald et al. (2015)	–	–	**86.7**
PathLSTM w/o reranker	**88.1**	**85.3**	**86.7**
System (global, single)	**P**	**R**	**F_1**
Björkelund et al. (2010)	88.6	85.2	86.9
Roth and Woodsend (2014)[3]	–	–	86.3
FitzGerald et al. (2015)	–	–	87.3
PathLSTM	**90.0**	**85.5**	**87.7**
System (global, ensemble)	**P**	**R**	**F_1**
FitzGerald et al. 10 models	–	–	87.7
PathLSTM 3 models	**90.3**	**85.7**	**87.9**

CoNLL-2009 in-domain test set.

System (local, single)	P	R	F_1
Björkelund et al. (2010)	75.7	72.2	73.9
Lei et al. (2015)	–	–	**75.6**
FitzGerald et al. (2015)	–	–	75.2
PathLSTM w/o reranker	**76.9**	**73.8**	75.3
System (global, single)	**P**	**R**	**F_1**
Björkelund et al. (2010)	77.9	73.6	75.7
Roth and Woodsend (2014)[3]	–	–	75.9
FitzGerald et al. (2015)	–	–	75.2
PathLSTM	**78.6**	**73.8**	**76.1**
System (global, ensemble)	**P**	**R**	**F_1**
FitzGerald et al. 10 models	–	–	75.5
PathLSTM 3 models	79.7	73.6	**76.5**

CoNLL-2009 out-of-domain test set.

Semantic Role Labeling: advanced

Unsupervised Induction of Frame-Semantic Representations

[Modi et al., 2012]

Motivation: jointly induce semantic frames and their roles without using pre-annotated data.

Approach: associate arguments with frame-specific argument keys (verb voice, arg position, syntactic rel to governor).

Semantic roles = clusters of arg keys; semantic frames are induced based on distribution.

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Semantic Role Labeling: advanced

Frame-semantic parsing:

Parameters:

for each frame $f = 1, 2, \ldots$:
- $\phi_f \sim DP(\gamma, H^{(P)})$ [distrib of lexical units]
- $B_f \sim CRP(\alpha)$ [partition of arg keys]
- for each role $r \in B_f$:
  - $\theta_{f,r} \sim DP(\beta, H^{(A)})$ [distrib of arg fillers]
  - $\psi_{f,r} \sim Beta(\eta_0, \eta_1)$ [geom distr for dup roles]

Data Generation:

for each frame $f = 1, 2, \ldots$:
- for each occurrence of frame f:
  - $p \sim \phi_f$ [draw a lexical unit]
  - for every role $r \in B_f$:
    - if $[n \sim Unif(0, 1)] = 1$: [role appears at least once]
      - **GenArgument**(f, r) [draw one arg]
      - while $[n \sim \psi_{f,r}] = 1$: [continue generation]
        - **GenArgument**(f, r) [draw more args]

GenArgument(f, r):
- $k_{f,r} \sim Unif(1, \ldots, |r|)$ [draw arg key]
- $x_{f,r} \sim \theta_{f,r}$ [draw arg filler]

Semantic Role Labeling: advanced

Results (induced vs FrameNet annotation):

Induced frames	FrameNet frames corresponding to the verbs
(rush::dash::tiptoe)	rush : [Self_motion](150) [Fluidic_motion](19) dash : [Self_motion](100) tiptoe : [Self_motion](114)
(ratify::sign::accede)	ratify : [Ratification](41) sign : [Sign_agreement](81) [Hiring](18) [Text_Creation](1) accede : [Sign_Agreement](31)
(crane::lean::bustle)	crane : [Body_movement](26) lean: [Change_posture](70) [Placing](22) [Posture](12) bustle : [Self_motion](55)
(cool::heat::warm)	cool : [Cause_temperature_change](27) heat: [Cause_temperature_change](52) warm: [Cause_temperature_change](41) [Inchoative_change_of_temperature](16)
(want::fib::dare)	want : [Desiring](105) [Possession](44) fib : [Prevarication](9) dare : [Daring](21)
(encourage::intimidate::confuse)	encourage : [Stimulus_focus](49) intimidate : [Stimulus_focus](26) confuse: [Stimulus_focus](45)

Semantic Role Labeling: advanced

Results (role-labeling vs frame-labeling):

	PU	CO	F1
Our approach	78.9	71.0	**74.8**
NoFrameInduction	79.2	70.7	**74.7**
SyntF	69.9	73.3	**71.6**

Role labeling performance.

	PU	CO	F1
Our approach	77.9	31.4	**44.7**
NoClustering	80.8	29.0	**42.7**

Frame labeling performance.

Issues: only 25% of verbs belong to induced multi-verb clusters. This could be due to the relatively small size of FrameNet, not enough evidence for clustering.

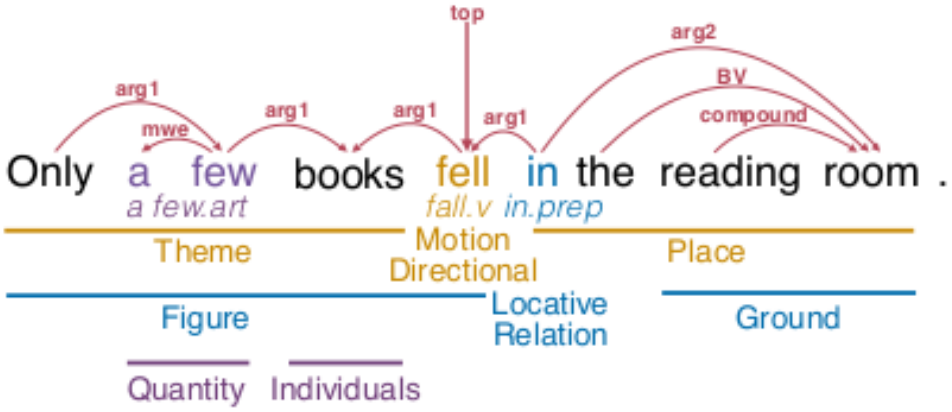
Semantic Role Labeling: advanced

Joint Semantic Parsers from Disjoint Data

[Peng et al., 2018]

Motivation: SRL with multiple datasets, combine **frame semantic** parsing with **dependency parsing**

Approach: use latent variables to extend cross-task part scoring if datasets do not overlap; learn cross-task using different formalisms (span vs dependency-based parsing); prune the space of cross task parts.



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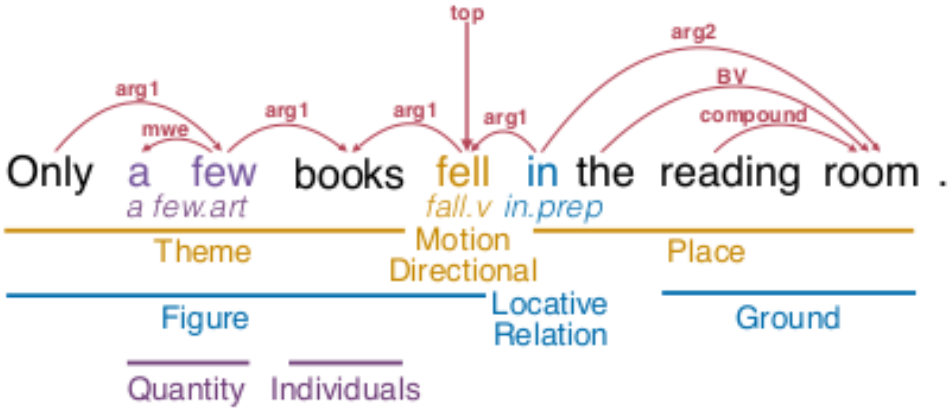

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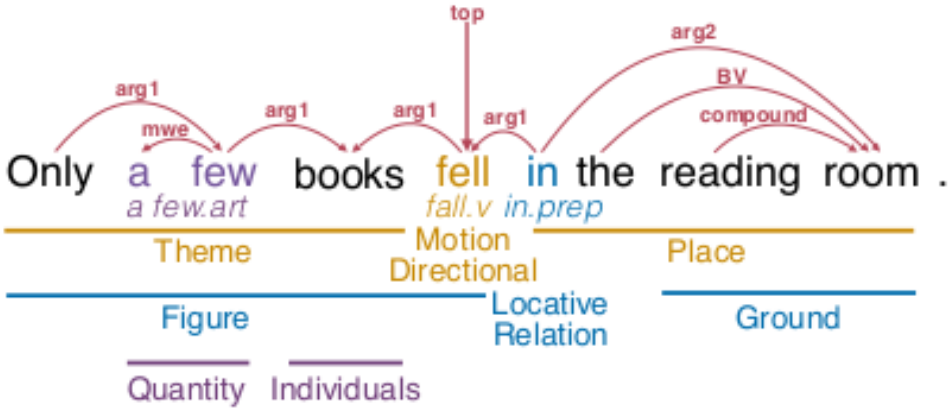


Semantic Role Labeling: advanced

Frame-Semantic Parsing (FrameNet style)

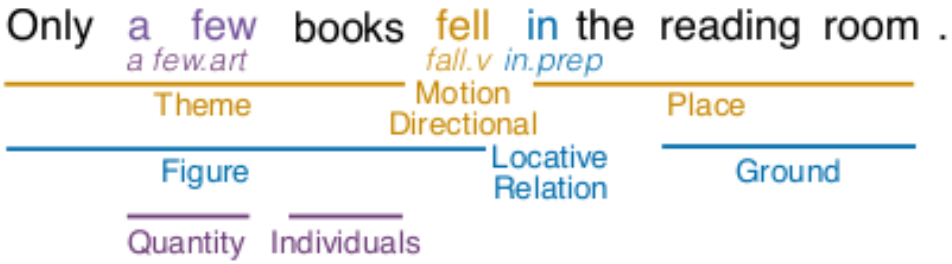
For a sentence X frame-semantic parse consists of:

1. Set of **targets** (short spans) that evokes a frame.

2. For each target t, the **frame f** that it evokes.

3. For each frame f , a set of **non-overlapping arg** spans in the sentence: arg = (i, j, r)

   start token index i; end token index j; role label r



Semantic Role Labeling: advanced

Semantic Dependency Parsing (PropBank style)

Each semantic dependency represents a labeled, directed edge between two words.

A single token with a **top label** indicates the main predicate.

head of an arc = **target** in frame semantics

destination = **argument**

label = **role**

Semantic Role Labeling: advanced

Idea:

(1)

Given a sentence *x* and target *t* (*l* for latent variable), find a set of valid **frame-semantic parses** as *Y(x, t, l)* and **dependency parses** as *Z(x)*.

$$(\hat{\mathbf{y}}, \hat{\mathbf{z}}) = \underset{(\mathbf{y},\mathbf{z}) \in \mathcal{Y}(\mathbf{x},t,\ell) \times \mathcal{Z}(\mathbf{x})}{\arg\max} S(\mathbf{y}, \mathbf{z}, \mathbf{x}, t, \ell).$$

Semantic Role Labeling: advanced

(2)

Learn a parameterized function *S* that scores candidate parses. **Jointly predict** a frame-semantic parse & dependency graph by selecting the best candidates.

Overall score *S* is a sum of frame SRL score S_f, dependency score S_d, and a cross-task score S_c

$$S(\mathbf{y}, \mathbf{z}, \mathbf{x}, t, \ell) = S_{\mathrm{f}}(\mathbf{y}, \mathbf{x}, t, \ell) + S_{\mathrm{d}}(\mathbf{z}, \mathbf{x}) + S_{\mathrm{c}}(\mathbf{y}, \mathbf{z}, \mathbf{x}, t, \ell).$$

Semantic Role Labeling: advanced

1. Learn contextualized token & span vectors with a **bidirectional LSTM & multilayer perceptrons**.

2. **Learn embeddings** for lexical units, frames, roles, and arc labels.

3. **Combine all representations** into a single scalar score using a (learned) low-rank multilinear mapping.

4. **Apply scoring function** to candidate arguments.

   Each candidate consists of:

   span + frame-dependent role + target + lexical unit

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Results:

Model	Prec.	Rec.	F_1
Roth	72.2	68.0	70.0
Täckström	75.4	65.8	70.3
FitzGerald	74.8	65.5	69.9
FitzGerald (10×)	75.0	67.3	70.9
open-SESAME	71.0	67.8	69.4
open-SESAME (5×)	71.2	70.5	70.9
Yang and Mitchell (REL)	77.1	68.7	72.7
†*Yang and Mitchell (ALL)	78.8	74.5	76.6
†This work (FULL)	80.4	73.5	76.8
†This work (FULL, 2×)	**80.4**	**74.7**	**77.4**
†This work (BASIC)	79.2	71.7	75.3
†This work (NOCTP)	76.9	74.8	75.8

Frame + SRL performance:
† is for models jointly predicting frames & arguments, other systems are two-stage pipelines.

Model	All	Ambiguous
Hartmann	87.6	-
Yang and Mitchell	88.2	-
Hermann	88.4	73.1
†This work (BASIC)	89.2	76.3
†This work (NOCTP)	89.2	76.4
†This work (FULL)	89.9	77.7
†This work (FULL, 2×)	**90.0**	**78.0**

Frame labeling performance.

Open Issues for SRL & Frames

1. **SRL degrades across different domains.**

   WSJ → Brown Corpus (12% decrease in F-measure)

2. SRL **depends on pre-processing** (POS-tagging, parsing).

   Errors can accumulate!

3. **Frame coverage is challenging.**

   FrameNet doesn’t provide universal generalizations.

Resources & Tools to try/play with

FrameNet: http://framenet.icsi.berkeley.edu/

PropBank: https://propbank.github.io/

Useful Tools:

MateTools (SRL):
https://code.google.com/archive/p/mate-tools/

MatePlus (SRL):

https://github.com/microth/mateplus

NeurboParser:

https://github.com/Noahs-ARK/NeurboParser

Next Topic Preview

Let’s move from rather static **frames** or **pictures** of events to more dynamic representations.

We can combine frames together & have more complex relations between them.

If we talk about **frames as pictures** than **scripts** are more about **movies**.

Next Topic Preview

Let’s learn **scripts**!

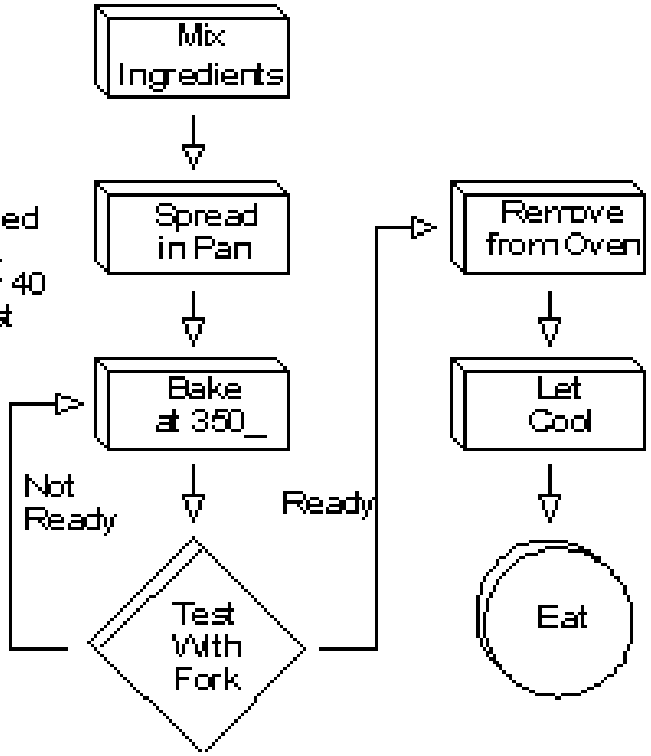
Recipe
CHOCOLATE CAKE

4 oz. chocolate	3 eggs
1 cup butter	1 tsp. vanilla
2 cups sugar	1 cup flour

Melt chocolate and butter. Stir sugar into melted chocolate. Stir in eggs and vanilla. Mix in flour. Spread mix in greased pan. Bake at 350_ for 40 minutes or until inserted fork comes out almost clean. Cool in pan before eating.

Program Code

```
Declare variables:
    chocolate   eggs      mix
    butter      vanilla
    sugar       flour
mix = melted  ((4*chocolate) + butter)
mix = stir (mix + (2*sugar))
mix = stir (mix + (3*eggs) + vanilla)
mix = mix + flour
spread (mix)
While not clean (fork)
bake (mix, 350)
```



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Peng H., Thomson S., Swayamdipta S., Smith N. A. Learning Joint Semantic Parsers from Disjoint Data. NAACL 2018.

Roth M., Lapata M. Neural Semantic Role Labeling with Dependency Path Embeddings. Proc. of ACL, 2016.

References

All screenshots with evaluation results & formulas were taken from the corresponding research papers.

Other pictures:

front page frame: https://myframe.co/frame-nlp/

p. 7 grapefruit: http://www.thepinsta.com/parts-of-a-grapefruit_5AmS7nbDfZzy3hI3dmJDj10PeCwJMiA%7CIeRHnYPzf64/

p. 4 semantics: https://translationmusings.com/2013/04/

p. 9 Russian breakfast: https://www.yummly.com/recipes/russian-breakfast

p. 9 Japanese breakfast: http://www.japansubculture.com/zeppin-%E7%B5%B6%E5%93%81-3-wachoshoku-japanese-breakfast-rules/

p. 11 white stuff: http://psilovepr.blogspot.com/2012/11/mini-post-3-linguistics_25.html

p. 62 cake flowchart: http://tharindu-rusira.blogspot.com/2011/09/algorithms-1.html