# Annotating and parsing to semantic frames: deep syntax for FrameNet parsing

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joint work with
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**G. de Chalendar, B. Sagot, P. Amsili** (for the French FrameNet)
**C. Ribeyre, D. Seddah, G. Perrier, B. Guillaume** (Deep syntax project)
**Olivier Michalon, Alexis Nasr** (FrameNet parsing)

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# Outline

1. Background and motivations
2. Deep syntax project
3. French FrameNet project
   - FrameNet's characteristics
   - Methodology
   - Evaluation and stats
   - Feedback: What was difficult?
4. Deep syntax for FrameNet parsing

(For ease of reading:
examples in English when strong French/English parallelism)

# Background and Motivations

# From syntactic treebanks to shallow semantic representations

Long history of building **syntactic treebanks** for French:

- French Treebank (Abeillé and al. 03)
- Treebanks for other domains:
  - Sequoia treebank (medical, Europarl, frwiki)
  - user-generated content (Seddah et al., 12)
  - Question Bank (Seddah and Candito, 16)
- Oral French treebanks
  - Rhapsodie (Lacheret et al., 14)
  - Orfeo (Kahane et al., 17)

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But obvious lack of a
more **semantically-oriented annotated resource** for French

# Objectives

Take a step towards semantic representation of sentences

Bottom-up approach

Aiming at **generalizing** over the expression of eventualities in texts by abstracting away from:

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Aiming at **generalizing** over the expression of eventualities in texts by abstracting away from:

- **morpho-syntactic variation**
  - $\longrightarrow$ **deep syntax project**
    make the most of syntactic dependency trees,
    using (almost) formal criteria only

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Move towards semantic representation of sentences

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Aiming at **generalizing** over the expression of eventualities in texts by abstracting away from:

- **lexical variation**
  - *A bomb* **exploded** *at 5 pm*
  - *A bomb* **blew up** *at 5 pm*
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- predicate-argument relations
  - $\longrightarrow$ **semantic roles**
    = classes of predicate-argument relations
  - at various levels of generalization
- we chose the **FrameNet** framework

## Normalizing syntactic representations: “Deep” syntax

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Joint work with G. Perrier, B. Guillaume, C. Ribeyre and D. Seddah
(Candito et al., 14; Perrier et al. 14)

**Bottom-up approach from syntactic parses**

- how to better take advantage of syntactic parses?
- (almost) without resorting to semantic disambiguation

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- (almost) without resorting to semantic disambiguation

- $\longrightarrow$ use of formal criteria mostly
- to **complete and normalize syntactic valency** of verbs, adjectives

# Related work

Close to the **"Deep Syntactic representations" in MTT** (Melčuk, 88)

- in particular the Spanish AnCora-UPF corpus (Mille et al, 13)

More recently: **Enhanced dependencies** in UD (guidelines of UD v2)

- inspired by Stanford dependencies (de Marneffe and Manning, 08)
- for English (Schuster and Manning, 16), French (Candito et al. 17) ...

Also related to more **semantically-oriented dependency graphs**:

- Tectogrammatical layer in Prague Dependency Bank (Czech, English) (Hajič et al., 06)
- DeepBank (English) (Flickinger et al., 12)
- SemEval 2014 Shallow Semantic parsing shared task (Oepen et al., 14)

# Normalizing syntactic representations: “Deep” syntax

Three main enhancements, concerning very well known phenomena:

- distributing shared arguments
- neutralizing syntactic alternations (diathesis alternation)
- (by-passing morpho/syntactic markers)

# “Deep” syntax: recovering shared arguments

**“Subjects” of non finite verbs: cases fully determined by syntax**

- raising/control verbs: ***Paul*** *seems/wants to* ***sleep.***
- control nouns, adjectives: ***Paul****'s desire to* ***sleep.***

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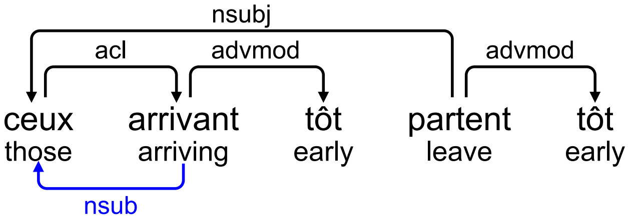
- raising/control verbs: ***Paul*** *seems/wants to* ***sleep.***
- control nouns, adjectives: ***Paul****'s desire to* ***sleep.***
- noun-modifying participles: ***those arriving*** *early /* ***arrived*** *at 9am.*
- etc...




$\longrightarrow$ dependency **graphs**

# "Deep" syntax: recovering shared arguments

**"Subjects" of non finite verbs: cases not fully determined by syntax**

- **Example: infinitive adverbial clauses**

*Il*$_{\mathbf{j}}$ *mangera avant de jouer*$_{\mathbf{j}}$
*He*$_{\mathbf{j}}$ *will-eat before to play*$_{\mathbf{j}}$
*« He will eat before playing »*

Not fully determined by syntax, but strong heuristics, e.g.:

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- When main verb is active, with non expletive subject
- $\Rightarrow$ Subject of infinitive = Subject of main verb
- in most cases (83% on Sequoia corpus)

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**Counter-example:**
*D'autres photos ont subi des retouches pour **accentuer** le drame.*
*'Other photos have undergone modifications to **accentuate** the drama.'*

# “Deep” syntax: recovering shared arguments

**Example: Arguments shared by coordinated predicates**

- **Paul** *is* ***starving*** *and* ***wants*** *to* ***eat***

- **Paul** *is* ***cooking*** *and* ***selling*** *pancakes*
- *Paul is* ***cooking*** *and* ***selling*** **pancakes**

- **Paul** *is* ***sleeping*** *and* ***selling*** *pancakes*

# “Deep” syntax: Neutralizing syntactic alternations

- recover **canonical grammatical functions**
  - $\approx$ the function you would get in active personal voice
  - inspired by Relational Grammar (Perlmutter and Postal, 83)
- for French:
  - massive for passive

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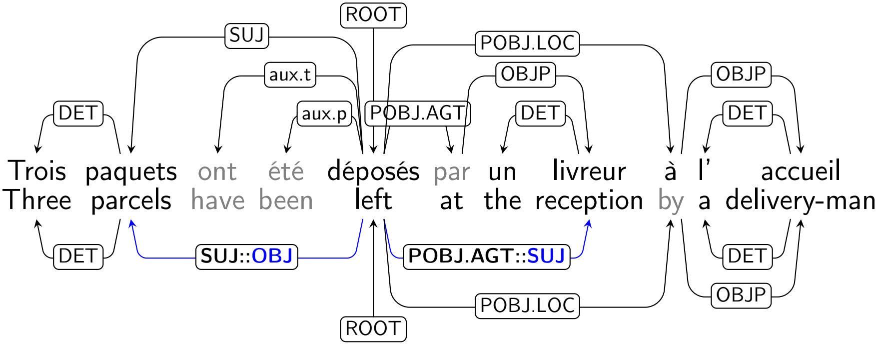

# “Deep” syntax: Neutralizing syntactic alternations

Key choice: use canonical **syntactic** labels

- As a way to limit **argument linking diversity**
- Main diathesis alternations (passive, medipassive, causative, impersonal...)
  - have strong syntactic constraints
  - but apply either independently of or for a wide range of underlying **semantic roles**
- $\longrightarrow$ cope with these alternations at the syntactic level
  - without presupposing disambiguation of predicates, nor link to lexical entries

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Versus

- I, II, III ... in deep syntactic representations of MTT
- plain semantic argument numbering ARG0, ARG1, ARG2...
  (e.g. PropBank, DeepBank)
  - argument numbering refers to a semantic-aware lexicon entry
- semantic roles AGENT, PATIENT, ADDRESSEE...
  (Prague Dependency Bank tectogrammatical layer)

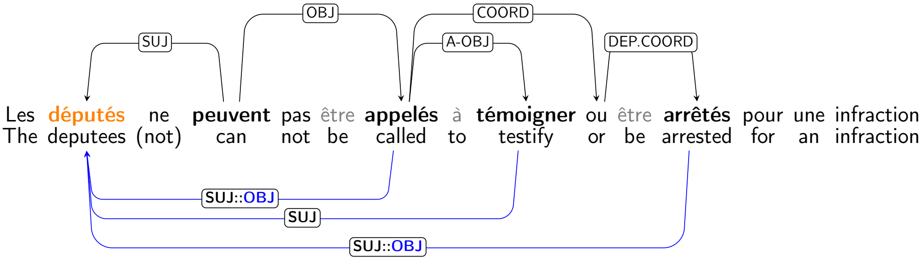
# Deep syntax: Neutralizing syntactic alternations

Handled alternations for French:

- passive
  - massive ( 18.3% non aux verbs are passives in Sequoia corpus )
  - unambiguous marking
- other alternations with morpho-syntactic marking
  - marking is in general ambiguous
  - but much rarer:
    - mediopassive ( 0.7% of non aux verbs in sequoia )
    - impersonal active ( 1% )
    - impersonal passive ( 0.27% )
    - causative ( 0.37% )
    - causative mediopassive ( absent )

# Deep syntax: interaction of phenomena

Raising, control, coordination, passive ... obvisouly interact




Note that alternation neutralization can concern deep edges!

# Deep syntax: obtaining deep syntactic graphs

**Gold data**: manually validated annotation on Sequoia (3099 sentences)

- manual annotation of 250 sentences
- to help development of deterministic graph-rewriting rules
  - Grew system (Guillaume et al. 2012)
  - OGRE system (Ribeyre et al. 2012)
- application on full Sequoia corpus (3099 sentences)
- adjudication of conflicts between the two systems
- manual checking of all infinitives and coordinations

- and further tuning of the graph-rewriting rules

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**Quantitative assessment of enhancements**:

- 200 sentences set
- $\approx$ 1000 edges correspond to **arguments of verbs**
- 18.9% are ADDED edges (not present in surface dependency tree)
- 13.9% are ALT (have a "neutralized" label)
- $ADDED \cup ALT$ represent 27.7% of the 1000 argumental edges

**Pseudo-gold data**: graph-rewriting rules applied to French Treebank (Ribeyre et al, 2014)

- Evaluation on 200 sentences shows quality is quite good (Fscore=97.7)

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**Deep syntax parsing**:

- pipeline surface parsing + deterministic rules
- or direct learning of graph parser (Ribeyre et al., 2015)

# French FrameNet

# Motivation

No large scale French data for (shallow) semantic analysis

⟶ let's build a resource:

- relying on **corpus evidence**
- **generalizing over:**
  - lexical items
  - predicate-to-argument relations (semantic roles)

- capitalizing on previous work for other languages

⟶ let's use the FrameNet framework (Baker et al. 1998; Fillmore 2007)

# FrameNet

Large scale "Instanciation" of the "Frame Semantics"
(Fillmore, 82)
for English
developed at Berkeley (Baker et al. 98, Fillmore et al. 03 ...)

- **frames** = schematic representations of speakers' knowledge of the situations underlying the meanings of LUs (Fillmore, 2007)
- a frame
  - can be evoked by lexical units ($\longrightarrow$ **triggers**)
    - e.g.: Commitment frame evoked by *promise.v*, *promise.n*, *oath.n* ...
  - whose semantic valency is describing using **frame-specific semantic role** names
    - Commitment; Speaker, Addressee, Message

# FrameNet

- Frame annotation = occurrence of a trigger evoking a frame, plus annotation of
  - **role fillers**: which portions of texts fill which semantic roles
  - syntactic information on role fillers

*John* ***PROMISED*** *Bill that the rights would be respected*

$\longrightarrow$ allowing to extract syntactico-semantic valency patterns

= **linking patterns**

# FrameNet: characteristics

## Structure: frames et relations entre frames

- $\approx$ 1200 frames
- linked by frame-to-frame relations (inheritance, perspective...)
- each frame-to-frame relation instance specifies role-to-role mappings
  - Complaining inherits Statement
  - Speaker $\leftrightarrow$ Complainer, Message $\leftrightarrow$ Complaint, Addressee $\leftrightarrow$ Addressee, ...

## English lexicon

- $\approx$ 13600 senses : lemma+pos / frame pairs

# FrameNet: characteristics

## Annotations

- lexicographic : examples from BNC, chosen in order to
  - capture variety of syntactic realization of semantic roles
  - and derive **linking generalizations**
  - 174000 annotated frame instances

- full-text : complete annotation of running text
  - 28000 annotated frame instances only
  - but much better training data (Das et al., 10))
  - because of natural distribution of senses and linking patterns

# FrameNet's key characteristics: Variable granularity of roles

- Well-known difficulty of defining a fixed and limited set of roles
- FrameNet's answer = **Frame-specific semantic roles**
  - $\oplus$ But coarser granularity can be derived from role-to-role mappings in frame-to-frame relation instances

# FrameNet's key characteristics: "semantics first" philosophy

Empirically grounded study of **syntax/semantic interface** is one of FrameNet's core objectives

But FrameNet's documentation (Rupenhoffer et al. 05) uses primarily **semantic criteria** for defining

- the perimeter of a frame (which generalizes over several lexemes)
- the set of roles of a frame ($\neq$Levin's classes, VerbNet...)
  - e.g. "Core" roles are those "necessary to the central meaning of the frame" (Fillmore, 2007)

# FrameNet's key characteristics: "semantics first" philosophy

- ⊖ lack of formal (syntactic) criteria to define the perimeter of frames
- ⊖ semantic granularity of the frames is partially arbitrary
  - certain frames contain synonyms only,
  - others allow more semantic variation

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- $\oplus$ semantic treatment of syntax/semantic mismatches ($\neq$ VerbNet)
- $\oplus$ a frame can generalize over LUs with different POS
  - e.g. the CAUSATION frame can be evoked by
  - *because.c*, *for.c*,
  - *cause.v*, *result.v*, ...
  - *cause.n*, *consequence.n*,
  - *because of.prep*, ...

# FrameNet's key characteristics: "semantics first" philosophy

- $\oplus$ roles less dependent on syntax, cf. **converse verbs** example
  - COMMERCE_SELL : sell.v, sale.n, auction.n,...
  - COMMERCE_BUY : buy.v, purchase.v, purchase.n ...
    - linked by "perspective" relation, and mapped roles

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- FrameNet / Propbank(Nombank) / VerbNet roles:
  - Buyer and Seller are stable in FrameNet
  - contrary to PropBank or VerbNet

I $_{\textbf{Buyer(Arg0/Agent)}}$ **bought** a Sovereign guitar $_{\textbf{Goods(Arg1/Theme)}}$
for 20 pounds $_{\textbf{Money(Arg3/Asset)}}$ from an absolute prat $_{\textbf{Seller(Arg2/Recipient)}}$

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China canceled its $_{\text{Seller(Arg0/Agent)}}$ **sale** of a uranium conversion facility $_{\text{Goods(Arg1/Theme)}}$ to Iran $_{\text{Buyer(Arg2/Recipient)}}$

# ASFALDA French FrameNet project

ANR funding, Oct 2012 to March 2016
Partners: Alpage, CEA-List, LIF, LLF, MELODI (IRIT)

The objective was to build

- a French FrameNet
- and a FrameNet semantic parser

# Methodology: coverage issues

Full coverage (of course) not reachable...

Which **frames** to work on? Which **lemmas**? Which **corpus** to annotate?

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Which **frames** to work on? Which **lemmas**? Which **corpus** to annotate?

Preliminary full-text annotation experiments, using English frames
Feedback: **extremely difficult** to understand the perimeter of a frame

$\longrightarrow$ Decision to focus on a few **notional domains**, but fully described

# Methodology: coverage issues

- **Commercial transactions**
- **Cognitive stances**
  - Position of a Cognizer concerning the truth value of a proposition
  - stative: who knows/believes what
  - inchoative (discover.v) / causative (convince.v)
- **Verbal communication**
- **Causality**

# Methodology: overview

- Frame structure and lexicon built in parallel
  - addition of syntactic criteria to better delimitate frames
- Corpus annotation
  - Pilot annotation to build the annotation guidelines
  - 4 domain experts + 6 annotators
  - 2 independent annotations + adjudication
  - $\longrightarrow$ again some further modifications of frames and lexicon!
- Extraction of data-driven lexicon

# Frames for French

- 105 frames for French built from English frames (FN 1.5)
  - 47 non modified English frames
  - 38 adapted to French / new frame delimitation criteria
  - 20 new frames created in order to complete a domain

| Domain | Nb frames | NB LUs (with at least one annotation) |
|---|---|---|
| **Commercial Transactions** | 19 | 99 |
| **Cognitive stances** | 44 | 442 |
| **Verbal Communication** | 47 | 411 |
| **Causality** | 11 | 285 |
| **All** | 105 | 873 |

- Note: some frames belong to several domains (e.g. FR_Attempt_suasion)

**Previous coverage strategies:**

- Exhaustive frame (senses) coverage for a given lemma
  - SALSA German FrameNet (Burchardt et al., 2006)
  - produces WSD-oriented data
- versus Exhaustive lexical coverage for a given frame
  - Berkeley FrameNet
  - information extraction oriented
  - $\longrightarrow$ **chosen in French FN, for the 4 selected domains**

**Possible coverage strategies:**

- Either select examples to maximize diversity of grammatical realizations
  - lexicographic approach
  - lexicographic examples of Berkeley FrameNet

# Corpus annotation

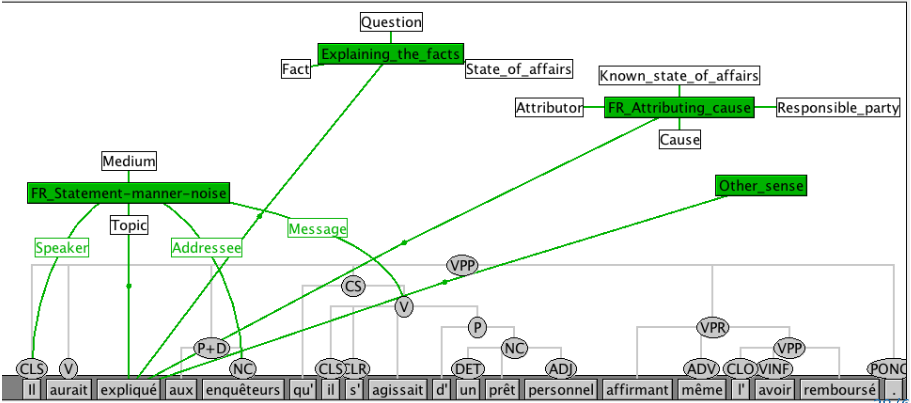
**Possible coverage strategies:**

- Either select examples to maximize diversity of grammatical realizations
  - lexicographic approach
  - lexicographic examples of Berkeley FrameNet
- or annotate running text: all lemmas of a text / first *xxx* occurrences of given lemma
  - preserves natural distribution
    - of senses
    - of grammatical characteristics of role fillers
  - used in full-text annotations of Berkeley FrameNet
  - SALSA German FrameNet
  - $\longrightarrow$ **French FN, first 100 occurrences in target corpus**

# Corpus annotation

- Annotation on syntactic (dependency) trees, in order to:
  - speed up annotation (but bias)
  - extract syntactico-semantic patterns
- 2 preexisting treebanks:
  - French Treebank (Abeillé et al. 03) and Sequoia (Candito & Seddah, 12)
  - $\approx$ 21500 sentences
  - Mainly news, plus medical, Europarl, Fr-wikipedia narrative texts
- Annotation at most first 100 occurrences of covered lemma+pos
- "Out_of_domain" dummy frame when sense is not covered

- Pilot annotation to develop annotation guide
- 2 independent annotations + adjudication (for 75% of data)
- 1 single annotation (by expert) for remaining 25%
  - Automatic pre-annotation of possible frames of the lemma
  - Salto tool (Burchardt et al., 2006)



# Evaluation: inter-annotator agreement

Between 2 independent annotations (75% of all annotations):

- for a trigger occurrence: Fscore for the frame choice
- for a frame chosen by both annotators: Fscore for role fillers

| | Nb trigger occurrences | % of Nouns | % of Verbs | Fscore inter-annotateur | | |
|---|---|---|---|---|---|---|
| | | | | Frame | Exact Role | Partial Role |
| | 17667 | 36 | 50 | 85.9 | 77.2 | 81.9 |
| Break-down by domain | | | | | | |
| Commercial | 3307 | 60 | 40 | 92.0 | 73.4 | 80.4 |
| Causality | 7691 | 30 | 48 | 79.2 | 74.2 | 80.4 |
| Cognitive stances | 7886 | 28 | 62 | 90.6 | 81.1 | 86.0 |
| Communication | 2221 | 23 | 76 | 89.6 | 82.3 | 87.5 |
| Break-down by trigger POS | | | | | | |
| V | 8834 | - | - | 87.6 | 82.8 | 87.1 |
| N | 6234 | - | - | 86.8 | 68.3 | 72.5 |
| other | 2509 | - | - | 77.7 | 74.6 | 82.1 |

# Stats (1.2 release)

http://asfalda.linguist.univ-paris-diderot.fr/frameIndex.xml

- $\longrightarrow \approx$ 16200 annotated frames (plus 8750 occurrences "Other_sense")

| | Nb distinct frames | Nb distinct lemma+POS | Nb senses | Nb annotated frames ($\neq$ Other_sense) |
|---|---|---|---|---|
| ALL | 105 | 873 | 1109 | **16167** |
| Fully covered lemma+POS | | 490 | | **7213** |
| Commercial | 19 | 90 | 99 | 2930 |
| Causality | 11 | 243 | 285 | 3895 |
| Cognitive | 44 | 372 | 442 | 5426 |
| Communication | 47 | 347 | 411 | 5233 |
| N | - | 296 | 346 | 5282 |
| V | - | 446 | 594 | 9165 |
| PREP | - | 35 | 43 | 674 |
| ADV | - | 26 | 42 | 407 |
| CONJ | - | 22 | 28 | 301 |
| ADJ | - | 43 | 48 | 234 |

# Semantic roles

- 421 frame-specific roles (for the 105 frames)
- grouped into 40 "macro-roles" defined at the domain level

See/get data at `http://asfalda.linguist.univ-paris-diderot.fr/frameIndex.xml`

# Frame structure and lexicon: feedback

- Division into frames is definitely the most difficult part
  - When starting from English frames: difficulty to understand differences between frames
  - Attempt to specify distinctive characteristics of frames

- $\longrightarrow$ Automatic induction ?
  - e.g. (Modi et al., 12)
  - with or without manual intervention

# Corpus FrameNet annotation: typical problems

Berkeley FrameNet: **chosen** examples $\longrightarrow$ Annotation difficulties not much documented

Very wide range of phenomena to handle

- divergences between litteral expression and interpretation
  - multi-word expressions (for triggers)
  - metaphors, ellipsis...
- lexical semantics
  - polysemy
  - nouns referring to a participant

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- lexical semantics
  - polysemy
  - nouns referring to a participant
- morpho-syntax / semantics interface
  - syntax/semantic mismatches
  - elliptic coordinations: arg cluster, head gapping...
  - ambiguous status of reflexive "se" clitic
    - diathesis alternation marker (mediopassive, neuter)
    - frozen
    - true reflexive ...

# Focus: predicative noun referring to a participant

(English examples for ease of reading)

**Relational nouns:**

*The precise **CAUSES** of multiple sclerosis are not yet known.*

**SYNTACTICALLY:**

- *causes* is **monovalent**: one PP

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(frame Causation; Cause, Effect)

*The precise **CAUSES** of multiple sclerosis are not yet known*

# Focus: predicative noun referring to a participant

In annotation guidelines, explicit distinction of:

- **referential uses** (most occurrences)
- **predicative uses**
  - $\longrightarrow$ in which we consider the trigger does not refer to the participant

Distinction pertaining for any noun:

- *Have you seen the unicorn?*
- *This animal is a unicorn.*

# Focus: predicative noun referring to a participant

## Referential uses

(frame Causation; Cause, Effect)

*The exact **CAUSES** of multiple sclerosis are not yet known*

*Liberia is still suffering from the **CONSEQUENCES** of 14 years of war*

# Focus: predicative noun referring to a participant

## Typical cases of predicative uses:

(frame Causation; Cause, Effect)

- **Apposition**:
  *First **CAUSE** of unemployment , short-term contract terminations are rising.*
- **Copulative sentence**:
  *Chronic venous insufficiency is the **CONSEQUENCE** of various abnormalities.*
- **Inverted copulative sentence**:
  *The **RESULT** of these measures has been to partially fill the deficit.*

# Event/Participant ambiguity

Typical case of a predicate that can refer to a role:
event/participant ambiguous nominalisations (or event/result).

(Commerce_buy; Buyer, Goods)

- *(...) to multiply its **PURCHASES** of car parts (...)*
  - event, buying act
- *How many times have you put down your **PURCHASES** willy-nilly, and trusted the cashier to do his job right?*
  - *purchases* refers to bought goods

# Deep syntax for FrameNet parsing

# FrameNet parsing

- WSD task: frame selection for an ambiguous trigger
- SRL task: role identification

Challenges

- Generalization over data
  - WordNet (e.g. Johansson et Nugues, 2007)
  - Distributed representations (e.g. Hermann et al. ACL 2014)
- Joint models (e.g. Yang and Mitchell, 2017)

# Deep syntax for FrameNet parsing

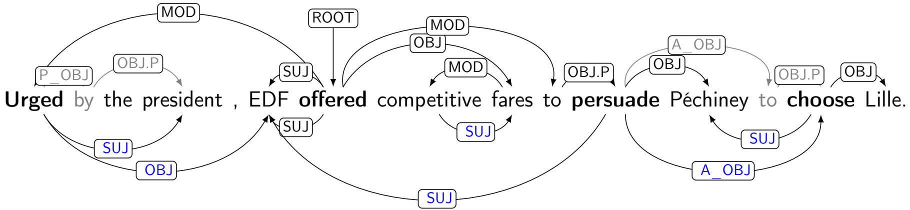
Joint work **Olivier Michalon**, Corentin Ribeyre, Alexis Nasr
(Michalon et al. Coling 2016)

- syntactic features known to be quite useful for SRL
  - since Gildea et Jurafsky, 2002
  - still true with neural networks approach
    (Hermann et al. 14; Yang and Mitchell 17)

- is it worth using deep syntax ?

# Deep syntax for FrameNet parsing

(arcs for determiners and punctuations not shown)



# Deep syntax for FrameNet parsing

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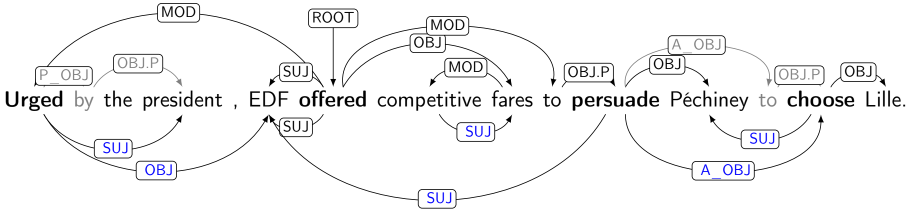


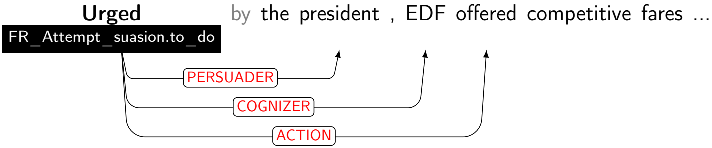

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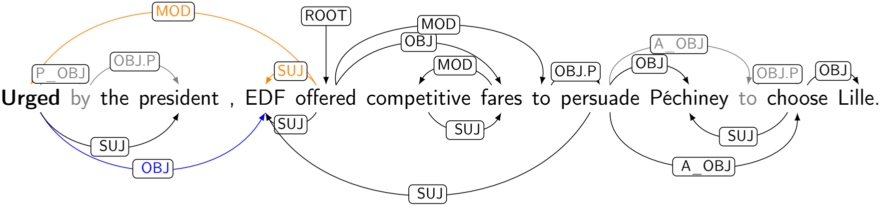


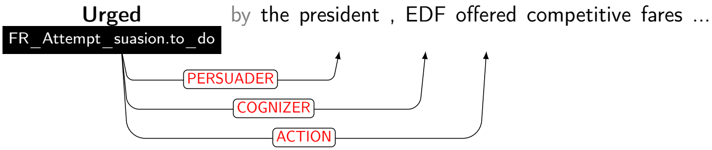


Syntactic path between "Urged" et "EDF" :

- surface: -mod,+suj
- deep: +obj

# Measuring the normalizing effect

Syntactic path between

- a predicate
- (the syntactic head) of a role filler

For a given role, deep syntactic paths are **more regular**:

**The distributions P(path to role filler | frame-specific role) are less scattered when using deep syntax.**

# Measuring the normalizing effect

Syntactic path between

- a predicate
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For a given role, deep syntactic paths are **more regular**:

**The distributions P(path to role filler | frame-specific role) are less scattered when using deep syntax.**

Indeed average entropy over all roles decreases:

- **1.65** with "classical" syntactic paths
- **1.32** with "deep" syntactic paths

# Measuring the normalizing effect

5 most frequent paths,
for the role fillers of verbal triggers

| surface syntax | | deep syntax | |
|---|---|---|---|
| (+suj) | 25.0% | (+suj) | 33.1% |
| (+obj) | 17.0% | (+obj) | 32.8% |
| (-mod) | 8.0% | (+a_obj) | 4.7% |
| (+obj,+obj.cpl) | 4.4% | (-mod) | 3.2% |
| (+a_obj,+obj.p) | 4.1% | (+mod,+obj.p) | 2.5% |
| Total | 58.6 % | Total | 76.2 % |

# Impact for FrameNet parsing

Very basic system (pipeline WSD + SRL, supervised linear classification)

- WSD : one classifier per ambiguous lemma
- SRL : one classifier per frame

Positive impact for FrameNet SRL, in particular for verbal triggers

| | Prec. | | Recall | | F-measure | |
|---|---|---|---|---|---|---|
| Input syntax | surf | deep | surf | deep | surf | deep |
| WSD (gold frame $\neq$ Other_sense) | 80.1 | 80.7 | 80.1 | 80.7 | 80.1 | 80.7 |
| SRL (for gold role filler heads) | 81.4 | 86.4 | 59.1 | 66.1 | **68.5** | **74.9** |

| Prec. | | Recall | | F-measure | |
|---|---|---|---|---|---|
| surf | deep | surf | deep | surf | deep |
| 80 | 80.5 | 80.8 | 80.9 | 80.4 | 80.7 |
| 75.7 | 80.3 | 51.6 | 59.0 | **61.3** | **68.0** |

Table: FastSem results for **verbs**, using **gold** (top) and **predicted** (bottom) surf and deep syntax.

# Perspectives

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  - Currently checking whether improvement carries over using a neural architecture

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- FrameNet construction:
  - very difficult and time consuming
  - coverage will never be sufficient
  - $\longrightarrow$ Frame induction
    - WSD + deep syntactic subcats + distributed representation of fillers...

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  - a lot of roles are not instantiated within sentence
  - recover role fillers in preceding sentences

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- Deep syntax:
  - Currently checking whether improvement carries over using a neural architecture
- FrameNet construction:
  - very difficult and time consuming
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  - $\longrightarrow$ Frame induction
    - WSD + deep syntactic subcats + distributed representation of fillers...
- Saturation of annotated frames
  - a lot of roles are not instantiated within sentence
  - recover role fillers in preceding sentences
- In the long term, still a long way for NLU
  - in particular: factivity of eventualities

Thank you!

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