Implicit Semantic Role Labelling

Computational Logics, Semantics and Pragmatics:
Semantic Interpretation.
2015

eman ta zabal zazu

Egoitz Laparra
***IXA** Group*
University of the Basque Country

ixa

Implicit Semantic Roles

Semantic Role Labelling (SRL)

- Identify the arguments or semantic roles of a predicate

[arg0 The network] [**vp lost**] *[arg1 $20 million] [arg3 on baseball this year]*.

- Traditional systems limit the search of the argument fillers to the elements that share a **syntactic relation** with the predicate.
- They miss cases that can be recoverable from the context.
  - They are **implicit**.

Implicit Semantic Roles

[arg0 The network] [**vp lost**] *[arg1 $20 million] [arg3 on baseball this year]*. It isn't clear how much those [**np losses**] may widen because of the short Series.

Quest Medical Inc said it adopted [*arg1 a shareholders' rights*] **[np plan]**

Implicit Semantic Roles

[arg0 The network] [**vp lost**] *[arg1 $20 million] [arg3 on baseball this year]*. It isn't clear how much those [**np losses**] may widen because of the short Series.

Imp-arg0: The network
Imp-arg1: $20 million
Imp-arg3: on baseball this year

Quest Medical Inc said it adopted [*arg1 a shareholders' rights*] **[np plan]**

Implicit Semantic Roles

[arg0 The network] [**vp lost**] *[arg1 $20 million] [arg3 on baseball this year]*. It isn't clear how much those [**np losses**] may widen because of the short Series.

Imp-arg0: The network
Imp-arg1: $20 million
Imp-arg3: on baseball this year

Quest Medical Inc said it adopted [*arg1 a shareholders' rights*] **[np plan]**

Imp-arg0: Quest Medical Inc

Early Works

Early studies on implict arguments described this problem as a special case of **anaphora resolution**

- [Palmer et al., 1986, Whittemore et al., 1991, Tetreault, 2002]
  - Selectional preferences
  - Semantic and syntactic constraints for each thematic role
  - Domain specific

More Recently

Task 10 of SemEval-2010 [Ruppenhofer et al., 2009]:

- Based on FrameNet
- Two sub-task
  - Argument annotation in a traditional SRL manner.
  - Filling elided arguments.

Gerber and Chai [2010, 2012].

- Based on NomBank
- Implicit arguments can increase the coverage of argument structures by **71%**.

More Recently

Task 10 of SemEval-2010 [Ruppenhofer et al., 2009]:

- VENSES++ [Tonelli and Delmonte, 2010]
  - Rule based anaphora resolution procedure and semantic similarity
- SEMAFOR [Chen et al., 2010]
  - Extended an existing semantic role labeler to enlarge the search window to other sentences

More Recently

Gerber and Chai [2010, 2012].

- Fully supervised approach:
  - Wide set of features:
    - Combination of SRL and Coreference Resolution
    - Relations between different roles
      - Same VerbNet class...
    - Most relevant ones are highly lexicalized

- [Silberer and Frank, 2012]
  - Adaptation of the same model for SemEvak-2010

In Summary

- Previous works face the task as special case of anaphora resolution:
  - Combining SRL and entity coreference.
- We also study other kinds of coreferential information.

In Summary

- Most succesful systems are fully supervised.
  - They require large amounts of training data for each predicate.
  - The training sets are too small or cover few predicates.
- Our approaches try to overcome the lack of training data.

First Approach

- Adapt coreference and pronoun resolution features.
  - Following previous works.
- Train a lexical independent model.
  - Generalizable to predicates with no training data.

First Approach

Task 10 of SemEval-2010 [Ruppenhofer et al., 2009]:

- Based on FrameNet
- Two sub-task
  - Argument annotation in a traditional SRL manner.
  - <u>Filling elided arguments.</u>

Gerber and Chai [2010, 2012].

- Based on NomBank

FrameNet

FrameNet [Baker et al., 1998] is a semantic resource that includes corpus annotations following the paradigm of Frame Semantics.

FrameNet

FrameNet [Baker et al., 1998] is a semantic resource that includes corpus annotations following the paradigm of Frame Semantics.

- **Frames** describe different events or scenarios.

Frame: **Residence**

FrameNet

FrameNet [Baker et al., 1998] is a semantic resource that includes corpus annotations following the paradigm of Frame Semantics.

- **Frames** describe different events or scenarios.
- ***Lexical-units*** (LU) are words evoke frames.

Frame: **Residence**

Lexical-units: occupy.v, dwell.v, resident.n, inhabitant.n ...

FrameNet

FrameNet [Baker et al., 1998] is a semantic resource that includes corpus annotations following the paradigm of Frame Semantics.

- **Frames** describe different events or scenarios.
- ***Lexical-units*** (LU) are words evoke frames.
- ***FrameElements*** (FE) are the arguments or roles.

Frame: **Residence**

Lexical-units: occupy.v, dwell.v, resident.n, inhabitant.n ...

FrameElements: *Resident, Location, Time, Manner ...*

FrameNet

FrameNet [Baker et al., 1998] is a semantic resource that includes corpus annotations following the paradigm of Frame Semantics.

- **Frames** describe different events or scenarios.
- ***Lexical-units*** (LU) are words evoke frames.
- ***FrameElements*** (FE) are the arguments or roles.
- ***Core FrameElements*** are the essential FEs of a frame.

Frame: **Residence**

Lexical-units: occupy.v, dwell.v, resident.n, inhabitant.n ...

FrameElements: *Resident, Location, Time, Manner ...*

Core FrameElements: *Resident, Location ...*

FrameNet

Not-filled FEs are called ***Null Instantiations*** (NI).

- If the fillers are inaccessible, the NIs are called ***Indefinite*** *Null Instantiations* (INI).
- When the fillers are recoverable, the NIs are called ***Definite*** *Null Instantiations* (DNI).

They own [a house together in St. Mary's]$_{Location}$. [A student]$_{Resident}$ has **dwelt**$_{\mathbf{Residence}}$ with [them]$_{Co-resident}$.

INI: *Time, Manner*

DNI: *Location*

Thus, the task of annotating implicit arguments following the FrameNet structures focuses just on **identifying and filling DNIs**.

SemEval-2010 task

Task 10 of SemEval-2010 [Ruppenhofer et al., 2009] was divided in two different sub-tasks:

- Argument annotation in a traditional SRL manner.
- <u>Filling null instantiations over the document.</u>

For the second sub-task a **gold-standar SRL** annotation is provided.

SemEval-2010 task

- Chapters extracted from two Arthur Conan Doyle’s stories.
  - Annotated using the frame-semantic structure of FrameNet 1.3
  - Null instantiations, the type of the NI and the corresponding fillers for each DNI.

data-set	**DNIs(solved)**	**Explicit FE**
train	303 (245)	2,726
test-13	158 (121)	1,545
test-14	191 (138)	1,688

Training-data sparseness:

- More cases annotated in the test-data

Sources of evidence

Adapt coreference and pronoun resolution features.

- Morpho-syntactic and Semantic Agreement
- Syntactic
- Discoursive
- Coreference chains

Study their behaviour in the **training** data-set.

Sources of evidence

Morpho-syntactic and Semantic Agreement:

- Semantic type
  - Top Ontology
- Part of speech

Learnt from explicit roles

Semantic type and POS

Frame#FrameElement	SemanticType	Probability
Expectation#Cognizer	Human	0.93
	Group	0.07
Residence#Location	Building	0.77
	Place	0.33
Attempt#Goal	Purpose	0.41
	UnboundEvent	0.37
	Object	0.13
	Part	0.09

Sources of evidence

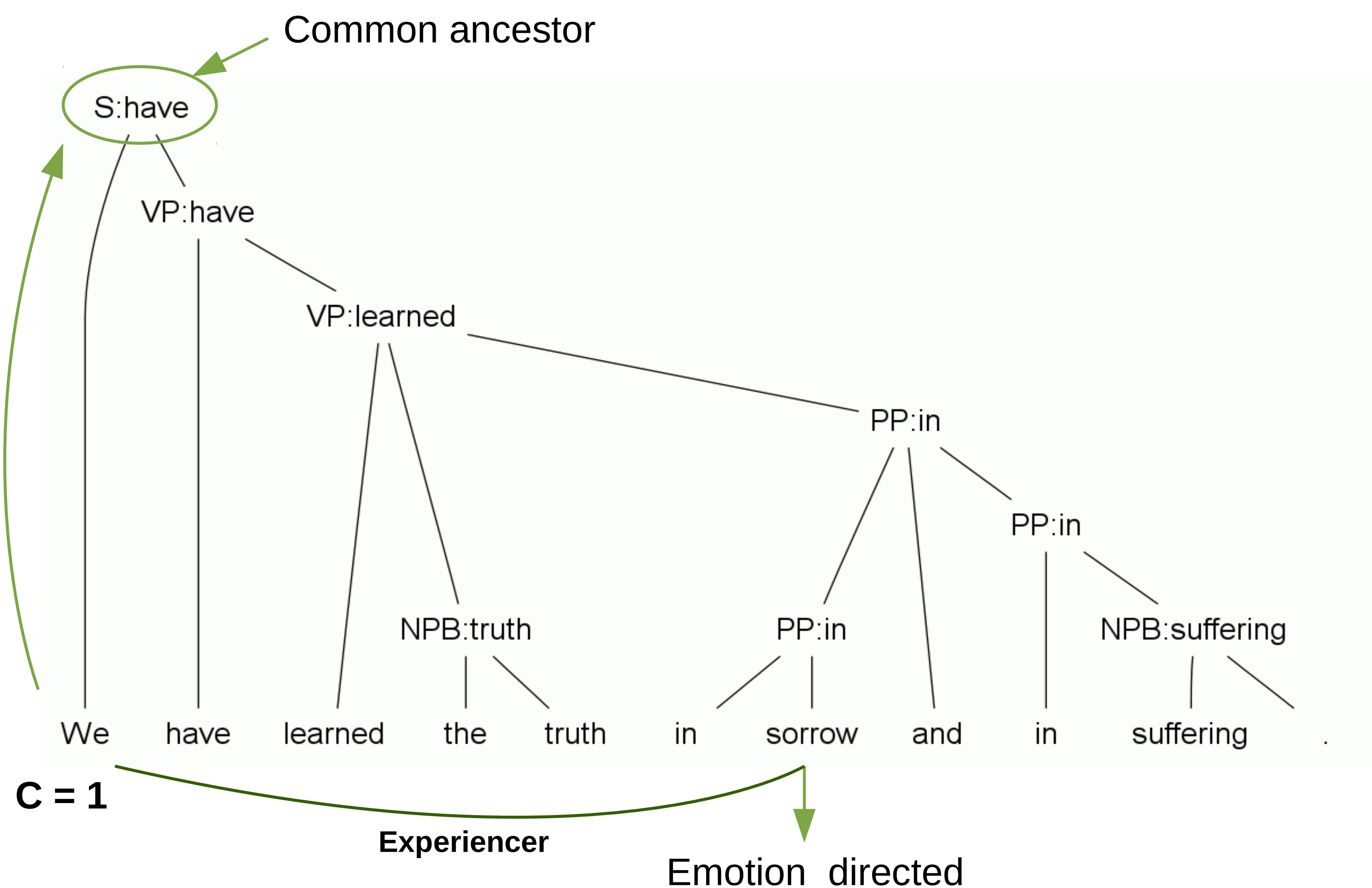
Syntactic features:

- Command
  - Based on C-command [Reinahrt, 1976]
- Nearness
  - Breadth-first search

Syntactic relations between the referenced entities.

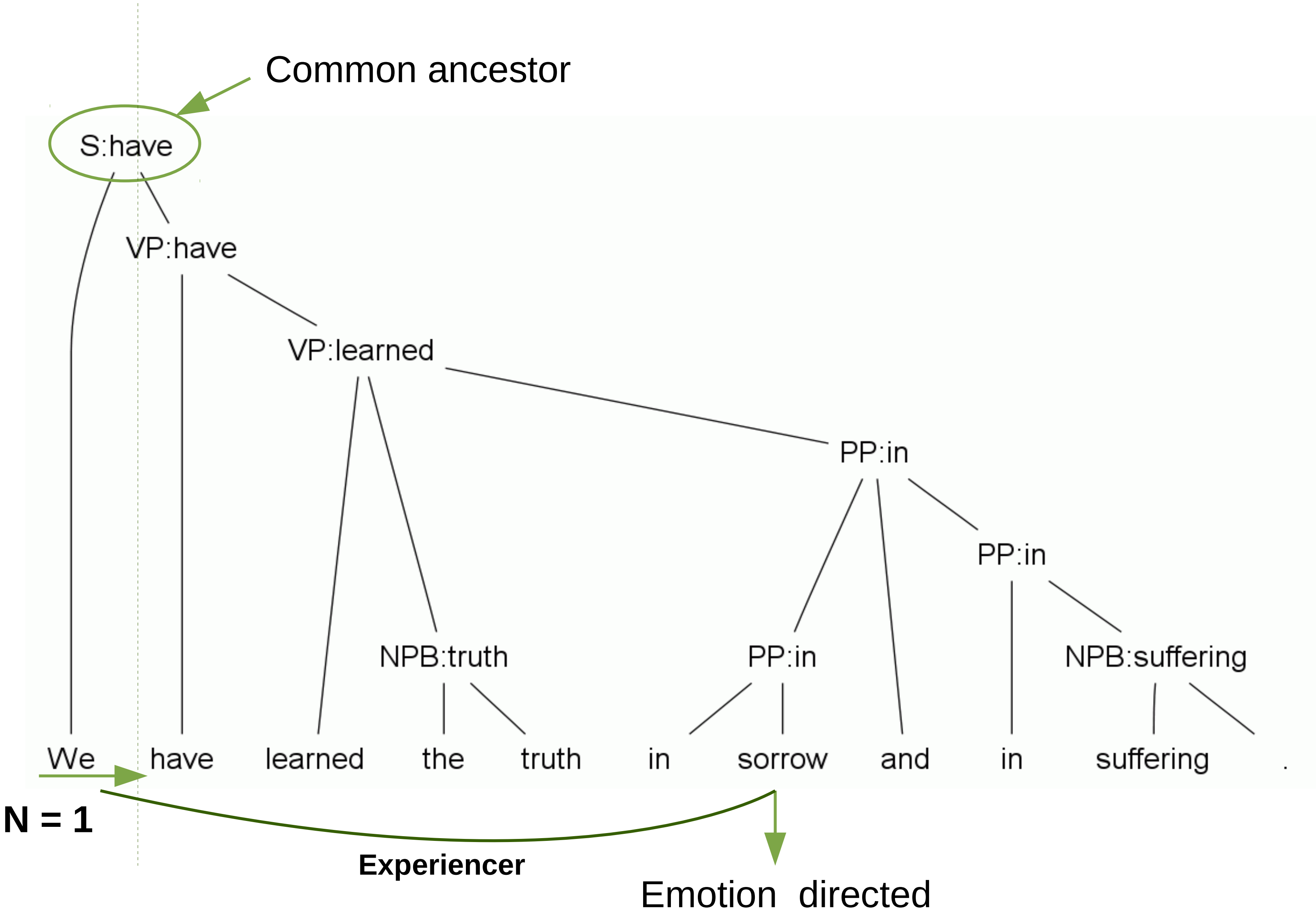
- Consituent tree
- We include an **artificial root node** covering all sentences

Command



Common ancestor
S:have
VP:have
VP:learned
PP:in
PP:in
NPB:truth
PP:in
NPB:suffering
We
have
learned
the
truth
in
sorrow
and
in
suffering
.
C = 1
Experiencer
Emotion_directed

Nearness


Common ancestor
S:have
VP:have
VP:learned
PP:in
PP:in
NPB:truth
PP:in
NPB:suffering
We
have
learned
the
truth
in
sorrow
and
in
suffering
.
N = 1
Experiencer
Emotion_directed

Sources of evidence

Discoursive features:

- Recency
  - **Sentence distance** between the lexical-unit of the target DNI and its referent
- Dialogue
  - We stablish two different levels of discourse:
    - Within dialogue
    - Outside dialogue (monologue)

Which **setences** are more likely to contain the filler of DNI

Dialogue

"I watched at the gate, same as you advised, Mr. Holmes" said our emisary, the discharged gardener.

"When the carriage came out I followed it to the station."

Dialogue

"I watched at the gate, same as you advised, Mr. Holmes" <u>said our emisary, the discharged gardener.</u>

"When the carriage came out I followed it to the station."

Outside dialogue (monologue)

Dialogue

"I watched at the gate, same as you advised, Mr. Holmes" said our emisary, the discharged gardener.

"When the carriage came out I followed it to the station."

Within dialogue

Dialogue

"I watched at [the gate]$_{\textit{Goal}}$, same as you advised, Mr. Holmes" said our emisary, the discharged gardener.

"When [the carriage]$_{\textit{Theme}}$ **came**$_{\textbf{Arriving}}$ [out]$_{\textit{Source}}$ I followed it to the station."

Target LU and filler of the DNI at the same level.

Sources of evidence

Coreference chains:

- Non-singleton
- Focus [Sidner, 1978]
  - If the filler is the last non-singleton
- Centering [Grosz et al., 1995]
  - Continuity of the focus
    - Cb(Un-1): The last focus
    - Cb(Un): The current focus
    - Cp(Un): The grammatical function of the current focus

Focus

But we know. We$_{\textit{Experiencer}}$ have learned the truth in **sorrow**$_{\textbf{Emotion\_directed}}$ and in suffering.

In this case there is not correferent between the last mention of ”We” and the LU ”sorrow”

- <u>In this case we say the filler is the focus</u>

Centering

But we know. We$_{\textit{Experiencer}}$ have learned the truth in **sorrow**$_{\textbf{Emotion\_directed}}$ and in suffering.

- Cb(Un-1) = ”we”
- Cb(Un) = ”We”
- Cp(Un) = ”We” (it is the subject of the sentence)

- Thus, the **centering** transition for the filler of *Experiencer:*
  - Continuing

Sources of evidence

Summary:

- The adaptations matches originals
- Most of the features are lexically independant

We evaluate this features in the test dataset

Solving the implicit arguments

Processing Steps:

1. Select the frame elements that are *Null Instantiations*.
2. Decide if the null instantiations are *Definite*.
3. In case of *definite null instantiation*, locate the corresponding filler.

For the first two steps, we have followed the strategy proposed in [Laparra and Rigau, 2012].

- 66% of DNIs in the testing data can be recognized correctly

Solving the implicit arguments

For the DNI filling we have trained a Naive-Bayes algorithm with the features studied.

- Maximum-likelihood
- No smoothing function

Thus, having a set of features *f*, for each DNI we select as filler the candidate *c* that satisfies:

$$\arg\max P(c) \prod_i P(f_i|c)$$

Score measures

Scorer provided for the NI SemEval subtask:

- **Precision** = true links predicted / total of links predicted
- **Recall** = true links predicted / total of true links
- **F-measure** = 2 * Precision * Recall / (Precision + Recall)

To evaluate the **overlap** of the predictions, the scorer computes **Dice coefficient**:

$$\textbf{NI linking overlap} = \frac{2|P \cap G|}{|P| + |G|}$$

- P is the number of words in the prediction
- G is the number of words in the gold-standard

Score measures

For the gold-standard annotation [*madam*], the next are considered as correct identifications.

- They have the same **head**

  [*madam*]

  [*no good will, madam*]

The first one, [*madam*], obtains better **overlap** value.

Evaluation

Results obtaining **coreference chains automatically** using Stanford CoreNLP:

System	**P**	**R**	**F1**	**Over.**
[Tonelli & Delmonte, 2010]]	-	-	0.01	-
[Chen et al., 2010]	**0.25**	0.01	0.02	-
[Tonelli & Delmonte, 2011]	0.13	0.06	0.08	-
[Silberer & Frank, 2012] no extra train	0.06	0.09	0.07	-
[Silberer & Frank, 2012] best	0.09	0.11	0.10	-
[Laparra & Rigau, 2012]	0.13	**0.25**	**0.19**	0.54
This work	0.14	0.18	0.16	**0.89**

Evaluation

Results using **gold-standard coreference** annotation:

System	P	R	F1	Over.
[Tonelli & Delmonte, 2010]				
[Chen et al., 2010]				
[Tonelli & Delmonte, 2011]				
[Silberer & Frank, 2012] no extra train	-	-	0.13	-
[Silberer & Frank, 2012] best	-	-	**0.18**	-
[Laparra & Rigau, 2012]				
This work	0.16	0.20	**0.18**	0.90

Evaluation

Results assuming **correct DNI identification** and **gold-standard coreference** annotation:

System	**P**	**R**	**F1**	**Over.**
[Silberer & Frank, 2012] no extra train	0.26	**0.25**	0.25	-
[Silberer & Frank, 2012] best	0.31	**0.25**	**0.28**	-
This work auto-coref	0.30	0.22	0.26	0.89
This work	**0.33**	0.24	**0.28**	0.89

Evaluation

Ablation tests over feature sets:

Source Set	P	R	F1	Over.
all	0.33	0.24	0.28	0.89
no-coref	0.30	0.22	0.25	0.86
no-semagree	0.22	0.22	0.22	0.90
no-discursive	0.29	0.22	0.25	0.82
no-syntactic	0.28	0.21	0.24	0.75

Semantic agreement features are the most relevant indentifiying the filler.

Syntactic features are the most relevant detecting the correct span of the filler.

Second Approach

- Combine entity and <u>event</u> coreference.
- Develop a deterministic algorithm.
  - No training data required.

Second Approach

Task 10 of SemEval-2010 [Ruppenhofer et al., 2009]:

- Based on FrameNet
- Two sub-task
  - Argument annotation in a traditional SRL manner.
  - <u>Filling elided arguments.</u>

Gerber and Chai [2010, 2012].

- Based on NomBank

Second Approach

Gerber and Chai [2010, 2012].

- We use the same dataset
  - Extension of the existing predicate annotations for NomBank and PropBank.
  - Only for **ten** different nominal predicates:
    - bid, cost, investment, investor, fund, loan, loss, plan, price, sale

- They pointed out that implicit arguments can increase the coverage of argument structures by **71%**.

Second Approach

Gerber and Chai [2010, 2012].

- Fully supervised approach:
  - Wide set of features:
    - Most relevant ones are highly lexicalized

- The model cannot be applied for other predicates without manually annotated training dataset

Second Approach

Dahl et al. [1987]

- Anaphoric mentions of nominal predicates
  - Arguments filled using referent mentions of the same predicate.

[*arg0 Wheat*] [**np prices**] remain stubbornly high and they 're likely to stay that way for months to come

Second Approach

Dahl et al. [1987]

- Anaphoric mentions of nominal predicates
  - Arguments filled using referent mentions of the same predicate.

arg0

[*arg0 Wheat*] [**np prices**] remain stubbornly high and **they** 're likely to stay that way for months to come

Second Approach

We apply a similar strategy:

- Assuming that in a coherent document the different mentions of a predicate (verbal or nominal) tend to refer to the same event.
- Spread the filler of an argument (explicit or implicit) to the rest of the instances of the predicate (verbal or nominal)

We move from entity coreference to event coreference

Second Approach

ImpAr algorithm:

- Deterministic approach
- It does not need implicit argument annotations for training
- Applicable for every predicate of PropBank and NomBank

Discoursive coherence of predicates

[arg0 The network] [**vp lost**] *[arg1 $20 million] [arg3 on baseball this year]*. It isn't clear how much those [**np losses**] may widen because of the short Series. ....

Discoursive coherence of predicates

arg0, arg1, arg3

[arg0 The network] [**vp lost**] *[arg1 $20 million]* *[arg3 on baseball this year]*. It isn't clear how much those [**np losses**] may widen because of the short Series. ....

Discoursive coherence of predicates

arg0, arg1, arg3

[arg0 The network] [**vp lost**] *[arg1 $20 million] [arg3 on baseball this year]*. It isn't clear how much those [**np losses**] may widen because of the short Series. ....

.... but the [**np losses**] could reach [*arg1 $ 250 million*] over four years and could go even higher

Discoursive coherence of predicates

arg0, arg1, arg3

[arg0 The network] [**vp lost**] *[arg1 $20 million] [arg3 on baseball this year]*. It isn’t clear how much those [**np losses**] may widen because of the short Series. ....

.... but the [**np losses**] could reach [*arg1 $ 250 million*] over four years and could go even higher

arg0, arg3

Filling arguments without explicit antecedents

For cases without explicit antecedents

- Filling the implicit arguments of a predicate has been described as a particular case of pronoun resolution [Silberer and Frank, 2012].
- We adapt a **pronoun resolution** algorithm:
  - RAP [Lappin & Leass, 1994]
    - Unsupervised
    - Salience factors according to syntactic information

Filling arguments without explicit antecedents

Factor type	weight
Sentence recency	100
Subject	80
Direct object	50
Indirect object	40
Head	80
Non-adverbial	50

Salience factors used by RAP [Lappin & Leass, 1994]

Filling arguments without explicit antecedents

0. Create a candidate list with the same sentence and the 2 previous ones
1. Apply two filters to rule out:
   a) Fillers of any arguments of the predicate.
   b) Candidates syntactically commanded by the predicate
2. Select the candidates that are semantically consistent
3. Assign a salience score to each candidate.
4. Sort the candidates by their proximity to the predicate.
5. Select the nearest candidate with the highest salience value.

Filling arguments without explicit antecedents

Quest Medical Inc said it adopted [*arg1 a shareholders' rights*] [**np plan**] in which rights to purchase shares of common stock will be distributed as a dividend to shareholders of record as of Oct 23.

Filling arguments without explicit antecedents

Quest Medical Inc said it adopted [~~*arg1 a shareholders' rights*~~] [**np plan**] in which rights to purchase shares of common stock will be distributed as a dividend to shareholders of record as of Oct 23.

- Filtering:
  - Fillers of other arguments

Filling arguments without explicit antecedents

Quest Medical Inc said it adopted [*arg1* ~~*a shareholders' rights*~~] [**np plan**] ~~in which rights to purchase shares of common stock will be distributed as a dividend to shareholders of record as of Oct 23.~~

- Filtering:
  - Fillers of other arguments
  - Syntactically commanded by the predicate

Filling arguments without explicit antecedents

Quest Medical Inc said it adopted [*arg1 ~~a shareholders' rights~~*] [**np plan**] ~~in which rights to purchase shares of common stock will be distributed as a dividend to shareholders of record as of Oct 23.~~

- Semantic consistency:
  - Selectional Preferences
    - Learnt from **explicit** arguments

Filling arguments without explicit antecedents

Quest Medical Inc said it adopted [*arg1* ~~*a shareholders' rights*~~] [**np plan**] ~~in which rights to purchase shares of common stock will be distributed as a dividend to shareholders of record as of Oct 23.~~

- Semantic consistency:
  - Selectional Preferences
    - Learnt from **explicit** arguments
    - **plan:***Arg0 = PERSON, ORGANIZATION*

Filling arguments without explicit antecedents

ORGANIZATION

Quest Medical Inc said it adopted [*arg1* ~~*a shareholders' rights*~~] [**np plan**] ~~in which rights to purchase shares of common stock will be distributed as a dividend to shareholders of record as of Oct 23.~~

- Semantic consistency:
  - Selectional Preferences
    - Learnt from **explicit** arguments
    - **plan:***Arg0 = PERSON, ORGANIZATION*

Filling arguments without explicit antecedents

ORGANIZATION

Quest Medical Inc said it adopted [*arg1 ~~a shareholders' rights~~*] [**np plan**] ~~in which rights to purchase shares of common stock will be distributed as a dividend to shareholders of record as of Oct 23.~~

- Assign to each candidate a set of salience factors that scores its prominence.
  - Same weights proposed by Lapping & Leass [1994]

Filling arguments without explicit antecedents

ORGANIZATION

Quest Medical Inc said it adopted [*~~arg1 a shareholders' rights~~*] [**np plan**] ~~in which rights to purchase shares of common stock will be distributed as a dividend to shareholders of record as of Oct 23.~~

– Assign to each candidate a set of salience factors that scores its prominence.
  - Same weights proposed by Lapping & Leass [1994]

Quest Medical Inc = **260**

Filling arguments without explicit antecedents

ORGANIZATION

Quest Medical Inc said it adopted [*arg1 a shareholders' rights*] [**np plan**] in which rights to purchase shares of common stock will be distributed as a dividend to shareholders of record as of Oct 23.

….

The [**np plan**] wasn't adopted in response to any known offers for the company.

Quest Medical Inc is also a candidate for posterior occurrences of missing *arg0* of **plan.**

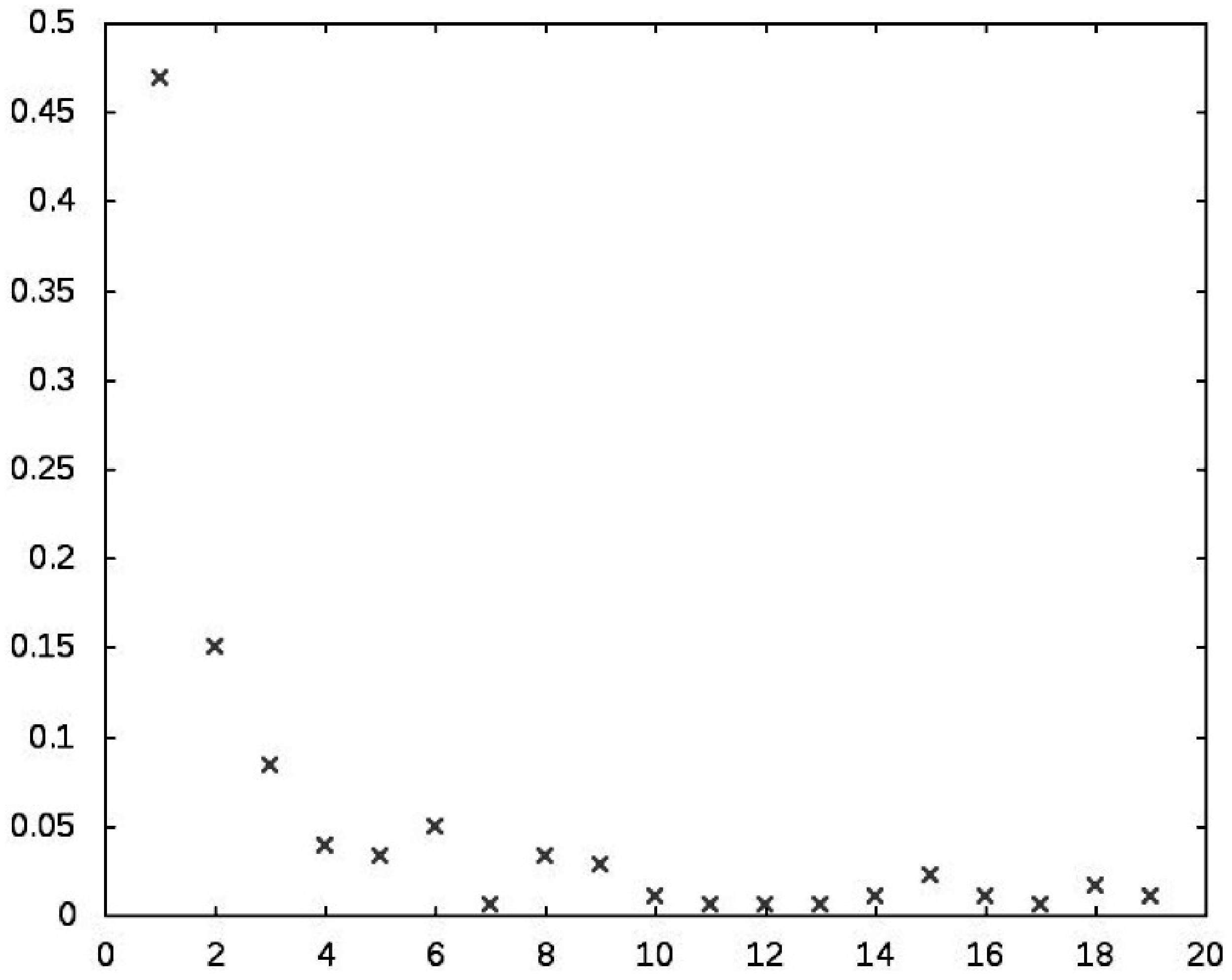
- With the same salience value

Damping the salience

Potential errors produced in the automatic selection process can spread to distant implicit instances.

- We include a damping factor *r* that is applied sentence by sentence to the salience value of the selected candidate.
- Strong value for *r* can harm excessively correct predictions.

Damping the salience



Distribution of sentence distances between implicit arguments with the same filler

Damping the salience

We mimic this curve using a dumping factor as:

$$r = 0.5^{d}$$

Given a salience score *s*, the value of the score in a following sentence, *s'* , is:

$$s' = s - 100 + 100 \cdot r$$

Damping the salience

Quest Medical Inc = **260**

- 1 sentence:

  $r = 0.5^1$

  $s' = 260 - 100 + 100 \cdot 0.5 = 210$

- 2 sentences:

  $r = 0.5^2$

  $s' = 260 - 100 + 100 \cdot 0.25 = 185$

Evaluation

Dataset by Gerber & Chai

- Gerber & Chai [2010]
  - Test dataset
- Gerber & Chai [2012]
  - Full dataset

- Gold SRL from PropBank and NomBank
- We include automatic syntactic and semantic annotations from CoNLL-2008 task.
- We use the same evaluation methodology

Evaluation

Dice coefficient, to evaluate the correct span of a filler:

$$\frac{2|Predicted \cap True|}{|Predicted| + |True|}$$

Ports of Call Inc. reached agreements to sell its remaining seven aircraft to buyers that weren’t disclosed.

True → [*arg1 buyers that weren’t disclosed*]
Prediction → [*arg1 to buyers*]

The prediction finds the head correctly but it is heavily penalized

Evaluation

Precision = sum of all prediction scores divided by the number of attempts.

Recall = sum of the prediction scores divided by the number of actual annotations.

F-measure is calculated as the harmonic mean of recall and precision.

Evaluation

			base.	Gerber & Chai			ImpAr		
	Inst.	Imp.	F_1	P	R	F_1	P	R	F_1
sale	64	65	36.2	**47.2**	**41.7**	**44.2**	45.7	33.4	38.6
price	121	53	15.4	36.0	32.6	34.2	**45.2**	**53.3**	**49.0**
investor	78	35	9.8	**36.8**	**40.0**	**38.4**	36.7	37.4	37.0
bid	19	26	32.3	23.8	19.2	21.3	**55.1**	**49.2**	**52.0**
plan	25	20	38.5	**78.6**	**55.0**	**64.7**	42.8	40.7	41.7
cost	25	17	34.8	**61.1**	**64.7**	**62.9**	52.9	47.4	50.0
loss	30	12	52.6	**83.3**	**83.3**	**83.3**	52.3	63.5	57.3
loan	11	9	18.2	**42.9**	**33.3**	**37.5**	28.6	20.0	23.5
investment	21	8	0.0	40.0	**25.0**	30.8	**92.9**	23.2	**37.1**
fund	43	6	0.0	14.3	16.7	15.4	**40.0**	**33.3**	**36.4**
Overall	437	246	26.5	44.5	40.4	42.3	**45.2**	**41.5**	**43.3**

- Gerber and Chei [2010]
  - Test dataset
- ImpAr gets better results
  - More uniform between different predicates

Evaluation

			base.	Gerber & Chai			ImpAr		
	Inst.	Imp.	F_1	P	R	F_1	P	R	F_1
sale	184	181	37.3	**59.2**	**44.8**	**51.0**	44.0	37.7	40.6
price	216	138	34.6	**56.0**	48.7	**52.1**	48.0	**52.7**	50.3
investor	160	108	5.1	**46.7**	39.8	**43.0**	24.7	26.0	25.3
bid	88	124	23.8	60.0	36.3	45.2	53.2	**42.2**	**47.0**
plan	100	77	32.3	**59.6**	**44.1**	**50.7**	52.7	**44.1**	48.0
cost	101	86	17.8	**62.5**	**50.9**	**56.1**	46.2	43.0	44.5
loss	104	62	54.7	**72.5**	**59.7**	**65.5**	56.4	54.2	55.2
loan	84	82	31.2	**67.2**	**50.0**	**57.3**	48.0	42.9	45.3
investment	102	52	15.5	32.9	**34.2**	**33.6**	**49.2**	20.8	29.2
fund	108	56	15.5	**80.0**	35.7	**49.4**	53.3	**42.9**	47.5
Overall	1,247	966	28.9	**57.9**	**44.5**	**50.3**	46.0	40.3	43.0

- Gerber and Chei [2012]
  - Full dataset
- Supervised gets better results,
  - Specially in terms of Precision
- ImpAr gets similar results to previous ones

Third Approach

- Apply semantic relations between events and roles .
  - Derived from knowledge bases.
- Extend the event coreference strategy used in ImpAr.

Third Approach

Task 10 of SemEval-2010 [Ruppenhofer et al., 2009]:

- Based on FrameNet
- Two sub-task
  - Argument annotation in a traditional SRL manner.
  - <u>Filling elided arguments.</u>

Gerber and Chai [2010, 2012].

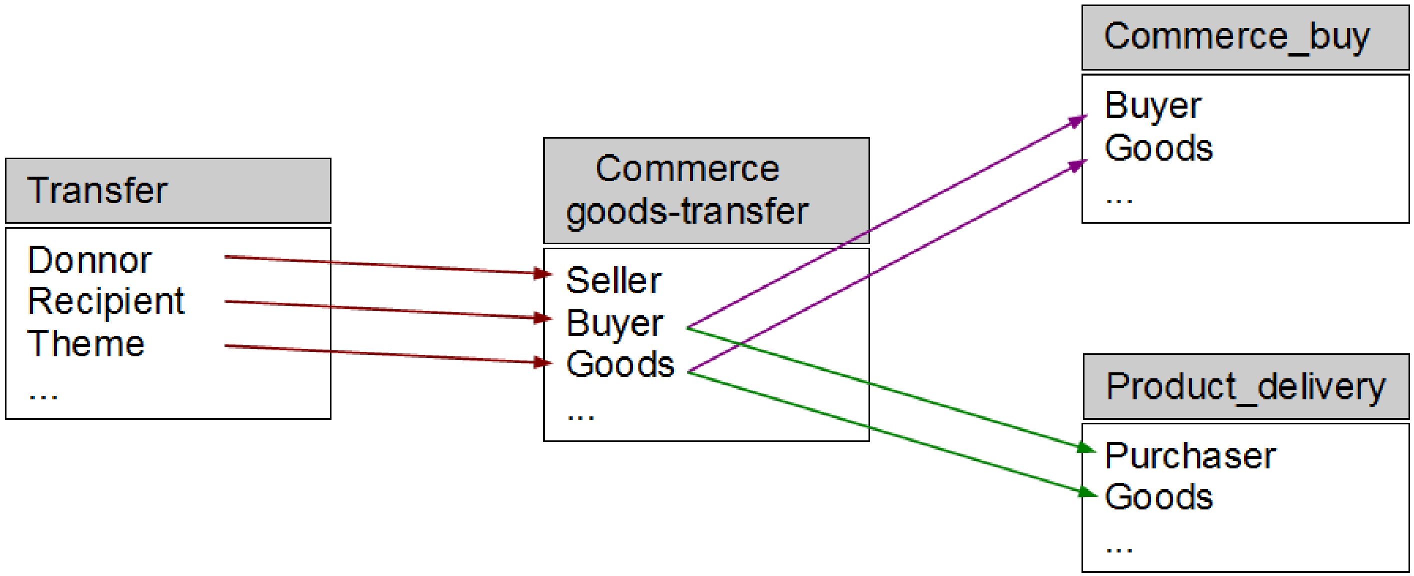
- Based on NomBank

Role implications for ISRL

A major reason is that investors already have sharply scaled back their **purchases** of stock funds since Black Monday...
...Stock-fund **sales** have rebounded in recent months...

purchase.01:A0 ⟷ **sale.01:A2**

Role implications for ISRL



- → *Inheritance*
- → *Perspective_on*
- → *Using*

Role implications for ISRL

- We include the relations of FrameNet into the ImpAr algorithm
  - ImpAr works with PropBank/NomBank
    - To project FN relations to PB/NB we use the mappings of the Predicate Matrix (López de Lacalle et al., 2014)

Role implications for ISRL

			None	SameFrame	All	Best
	Inst.	Imp.	F_1	F_1	F_1	F_1
sale	184	181	40.6	40.6	43.0	**45.0**
price	216	138	50.3	50.3	54.7	**55.5**
investor	160	108	25.3	25.3	25.3	25.3
bid	88	124	47.0	47.0	47.0	47.0
plan	100	77	**48.0**	45.0	42.0	45.0
cost	101	86	**44.5**	**44.5**	44.2	44.2
loss	104	62	**55.2**	54.7	54.7	54.7
loan	84	82	45.3	45.3	45.3	45.3
investment	102	52	29.2	29.2	29.2	29.2
fund	108	56	47.5	47.5	47.5	47.5
Overall	1,247	966	43.0	42.7	43.5	**44.5**

– FrameNet relations affect very little

Role implications for ISRL

	Inst.	Imp.	None F_1	SameFrame F_1	All F_1	Best F_1
sale	184	181	40.6	40.6	43.0	**45.0**
price	216	138	50.3	50.3	54.7	**55.5**
investor	160	108	25.3	25.3	25.3	25.3
bid	88	124	47.0	47.0	47.0	47.0
plan	100	77	**48.0**	45.0	42.0	45.0
cost	101	86	**44.5**	**44.5**	44.2	44.2
loss	104	62	**55.2**	54.7	54.7	54.7
loan	84	82	45.3	45.3	45.3	45.3
investment	102	52	29.2	29.2	29.2	29.2
fund	108	56	47.5	47.5	47.5	47.5
Overall	1,247	966	43.0	42.7	43.5	**44.5**

- FrameNet does not cover all these predicates
  - Investor, bid or fund do not appear in FN

Role implications for ISRL

			None	SameFrame	All	Best
	Inst.	Imp.	F_1	F_1	F_1	F_1
sale	184	181	40.6	40.6	43.0	**45.0**
price	216	138	50.3	50.3	54.7	**55.5**
investor	160	108	25.3	25.3	25.3	25.3
bid	88	124	47.0	47.0	47.0	47.0
plan	100	77	**48.0**	45.0	42.0	45.0
cost	101	86	**44.5**	**44.5**	44.2	44.2
loss	104	62	**55.2**	54.7	54.7	54.7
loan	84	82	45.3	45.3	45.3	45.3
investment	102	52	29.2	29.2	29.2	29.2
fund	108	56	47.5	47.5	47.5	47.5
Overall	1,247	966	43.0	42.7	43.5	**44.5**

– FrameNet does not cover all these predicates
  - Investment does not have the same meaning

Role implications for ISRL

			None	SameFrame	All	Best
	Inst.	Imp.	F_1	F_1	F_1	F_1
sale	184	181	40.6	40.6	43.0	**45.0**
price	216	138	50.3	50.3	54.7	**55.5**
investor	160	108	25.3	25.3	25.3	25.3
bid	88	124	47.0	47.0	47.0	47.0
plan	100	77	**48.0**	45.0	42.0	45.0
cost	101	86	**44.5**	**44.5**	44.2	44.2
loss	104	62	**55.2**	54.7	54.7	54.7
loan	84	82	45.3	45.3	45.3	45.3
investment	102	52	29.2	29.2	29.2	29.2
fund	108	56	47.5	47.5	47.5	47.5
Overall	1,247	966	43.0	42.7	43.5	**44.5**

– The role relations for sale and price seem to have an important effect

Role implications for ISRL

			None	SameFrame	All	Best
	Inst.	Imp.	F_1	F_1	F_1	F_1
sale	184	181	40.6	40.6	43.0	**45.0**
price	216	138	50.3	50.3	54.7	**55.5**
investor	160	108	25.3	25.3	25.3	25.3
bid	88	124	47.0	47.0	47.0	47.0
plan	100	77	**48.0**	45.0	42.0	45.0
cost	101	86	**44.5**	**44.5**	44.2	44.2
loss	104	62	**55.2**	54.7	54.7	54.7
loan	84	82	45.3	45.3	45.3	45.3
investment	102	52	29.2	29.2	29.2	29.2
fund	108	56	47.5	47.5	47.5	47.5
Overall	1,247	966	43.0	42.7	43.5	**44.5**

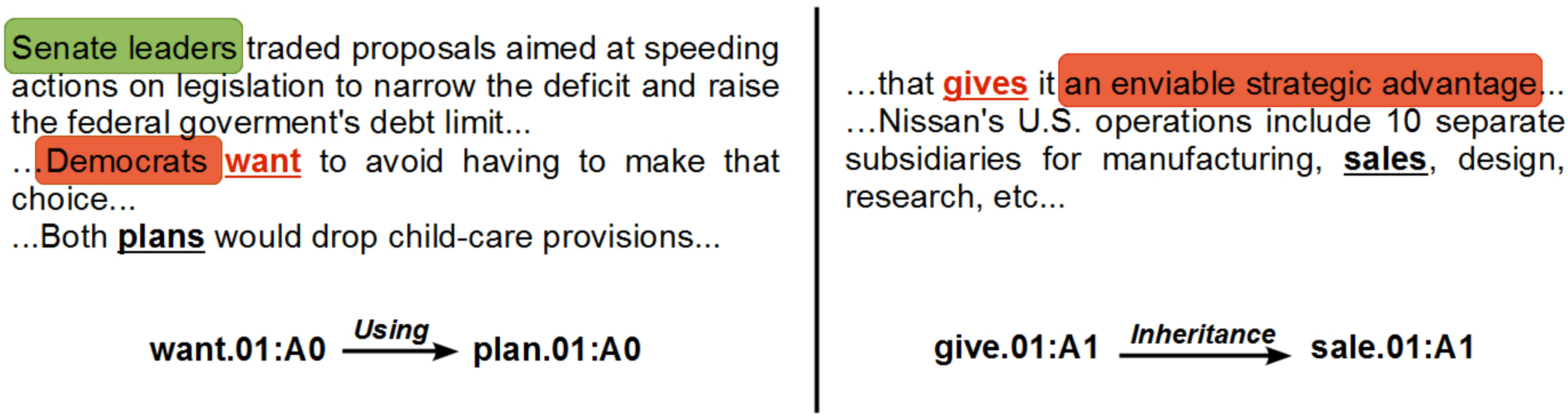
– Best: Ruling out *Inheritance* and *Using* relations

Role implications for ISRL

	ImpAr	IU	Best
sale	40.6	42.0	**45.0**
price	50.3	49.6	**55.5**
cost	**44.5**	44.2	44.2
plan	**48.0**	41.7	45.0
loss	**55.2**	54.7	54.7
Overall	43.0	42.5	**44.5**

- Best: Ruling out *Inheritance* and *Using* relations
- IU: Only *Inheritance* and *Using* relations

Role implications for ISRL



- *Using* and *Inheritance* relate frames that do not belong to the same domains or scenario.

Role implications for ISRL

- Resources that contain entailment relations derived from FrameNet
  - LexPar (Coyne and Rambow, 2009)
    - WordNet synonyms and hyponyms
    - FrameNet Perspective_on relations
  - FRED (Aharon et al., 2010)
    - Inheritance, Cause, Perspective_on relations
    - Not for all the predicates

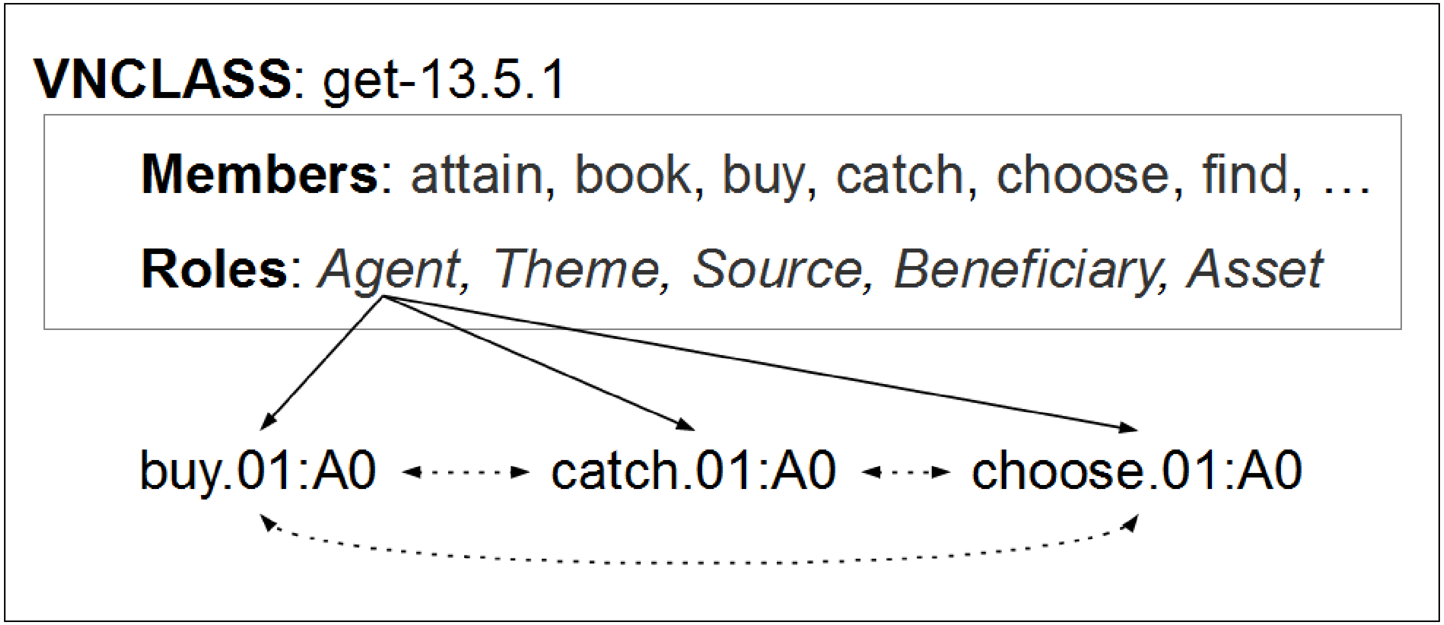
Role implications for ISRL

	None	Best	LexPar	FRED
P	46.0	**46.3**	45.6	45.8
R	40.3	**42.7**	41.2	41.3
F	43.0	**44.5**	43.3	43.4

- The conditions for generating LexPar and FRED restric the potential contributions of FrameNet relations for ISRL.

Role implications for ISRL

- VerbNet (Kipper, 2005)
  - Sets of semantically related verbs that share the same roles.



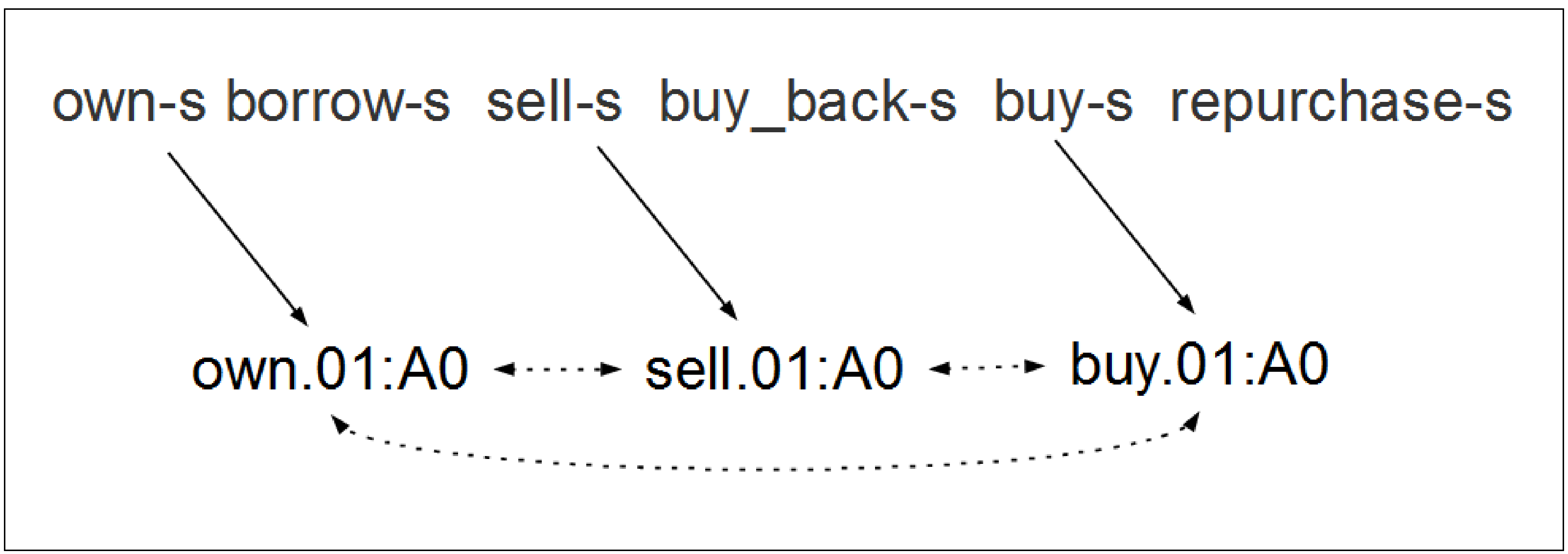
Role implications for ISRL

	None	Best	VNC	VNSC
P	46.0	**46.3**	42.9	44.7
R	40.3	**42.7**	39.3	39.8
F	43.0	**44.5**	41.0	42.1

- Although the verbs included in a class of VerbNet are semantically related, they do not necessarily belong to the same domain or scenario.
  - get, buy

Role implications for ISRL

- Narrative schemas (Chambers and Jurafsky, 2010)
  - Sequences of events where the subjects or the objects are the same entity



Role implications for ISRL

	None	Best	ns6t0	ns6t12	ns6t14	ns8t0	ns12t0	ns12t35
P	46.0	**46.3**	24.1	28.4	45.0	26.6	32.7	33.2
R	40.3	**42.7**	24.7	28.4	40.2	26.9	32.7	33.1
F	43.0	**44.5**	24.4	28.4	42.4	26.7	32.7	33.1

- Narrative schemas encode temporal ordering, not implication between roles.
  - sell.01:A0 ---> buy.01:A0

Implicit Semantic Role Labelling

Computational Logics, Semantics and Pragmatics:
Semantic Interpretation.
2015

eman ta zabal zazu

Egoitz Laparra
***IXA** Group*
University of the Basque Country

ixa