Universitat Politècnica de Catalunya
Ph.D. Program on Artificial Intelligence

Learning and Inference in Phrase Recognition: A Filtering-Ranking Architecture using Perceptron

Ph.D. Dissertation by

Xavier Carreras Pérez

advised by
Lluís Màrquez Villodre

Outline

- Introduction: Phrase Recognition
- Learning Methods for Text Analysis Tasks
- Filtering-Ranking Architecture
- Systems and Results on Syntactic-Semantic Parsing
- Conclusion and Future Research

Natural Language Learning for Text Analysis

- NLL: Learning as a central mechanism to process natural language
- Text Analysis: a fundamental task in NLP
  - ⋆ Consists of recognizing the linguistic structures underlying text
  - ⋆ Useful for applications dealing with language:
    - ▷ Intelligent Information Access (e.g., Question-Answering)
    - ▷ Machine Translation Systems
    - ▷ . . .

Phrase Recognition

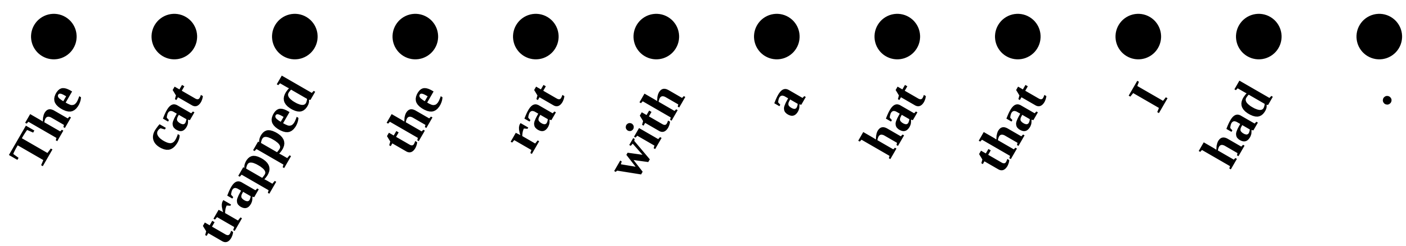
- A family of text analysis tasks
- What is a phrase, in general?

  a group of words performing a function as a unit
- Many problems in Natural Language consist of recognizing phrases in a sentence
- $a.k.a.$ segmentation problems, tagging and parsing problems

Syntactic Parsing

- Phrase = constituent : a group of words performing a syntactic function
- Several levels/versions of the problem:
  - ⋆ Full Parsing: recover the full syntactic tree
  - ⋆ Partial Parsing: recover only some syntactic elements:
    - ▷ Chunking: recognize chunks, i.e., base non-recursive phrases
    - ▷ Noun-Phrase recogniton: recognize the structure of NPs
    - ▷ Clause Identification: recover the clauses (usually in hierarchy)
    - ▷ . . .

Phrase Recognition in Partial Syntactic Analysis



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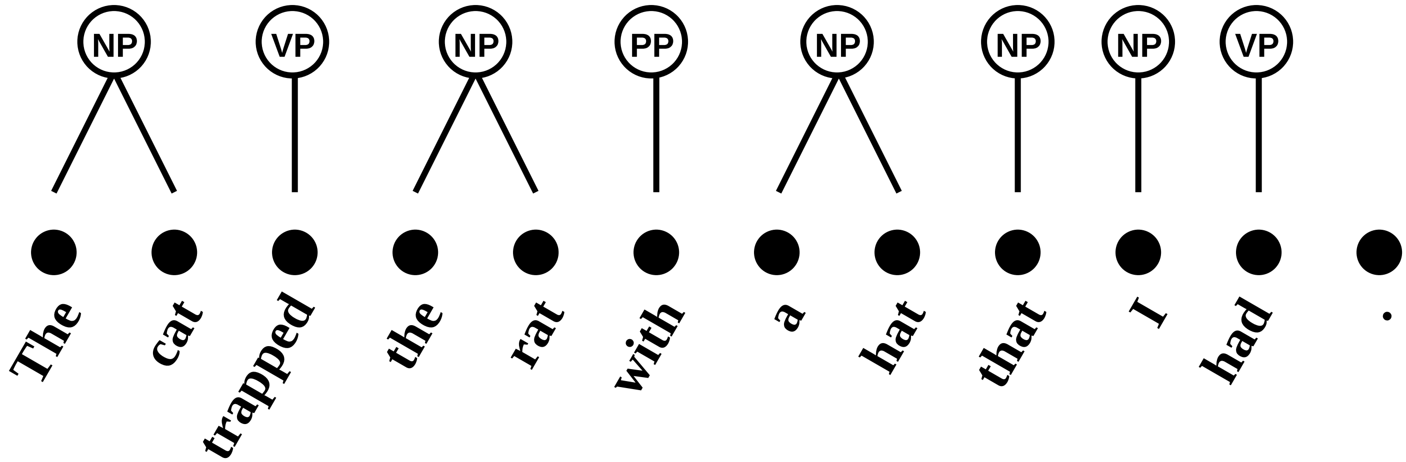

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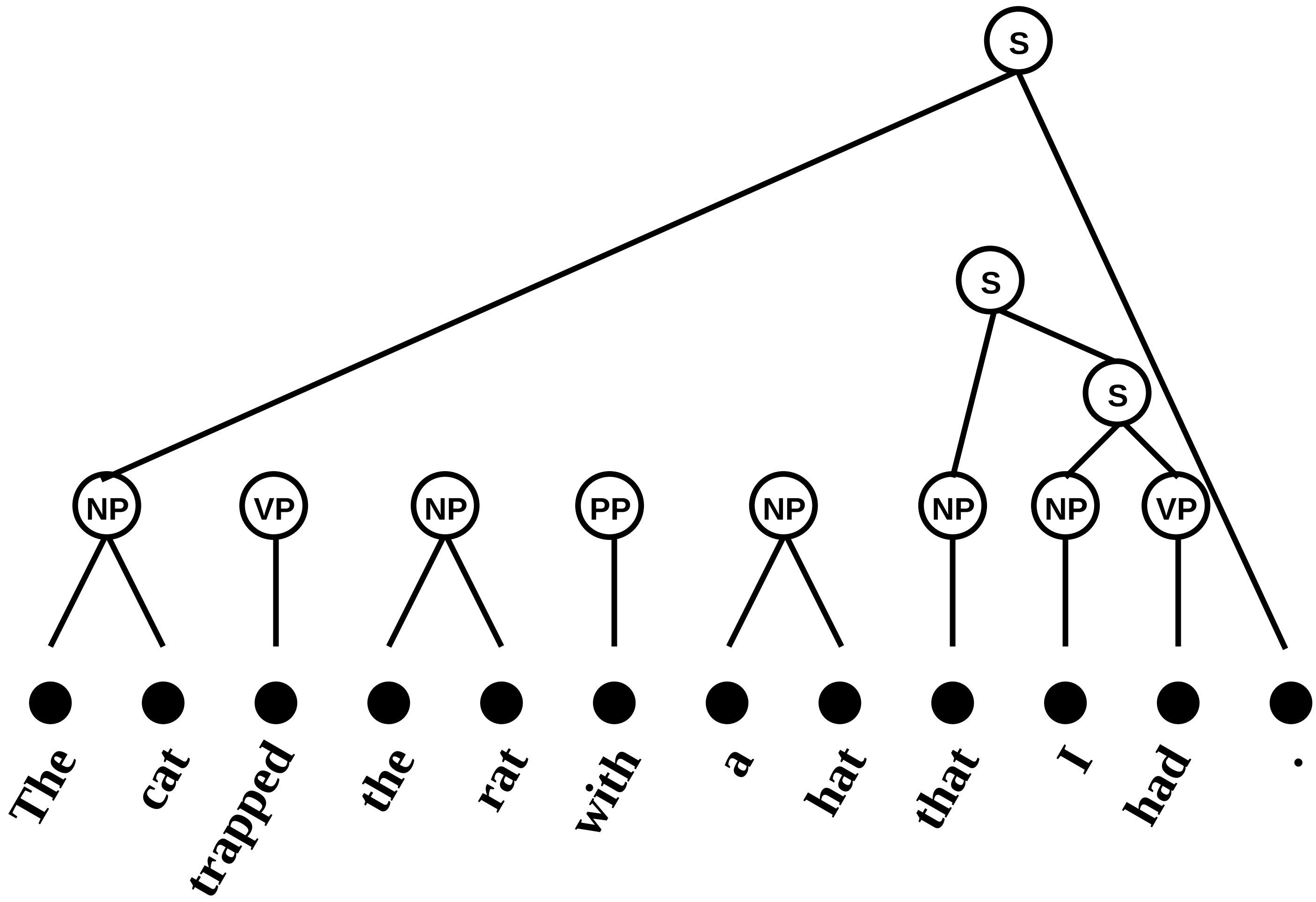
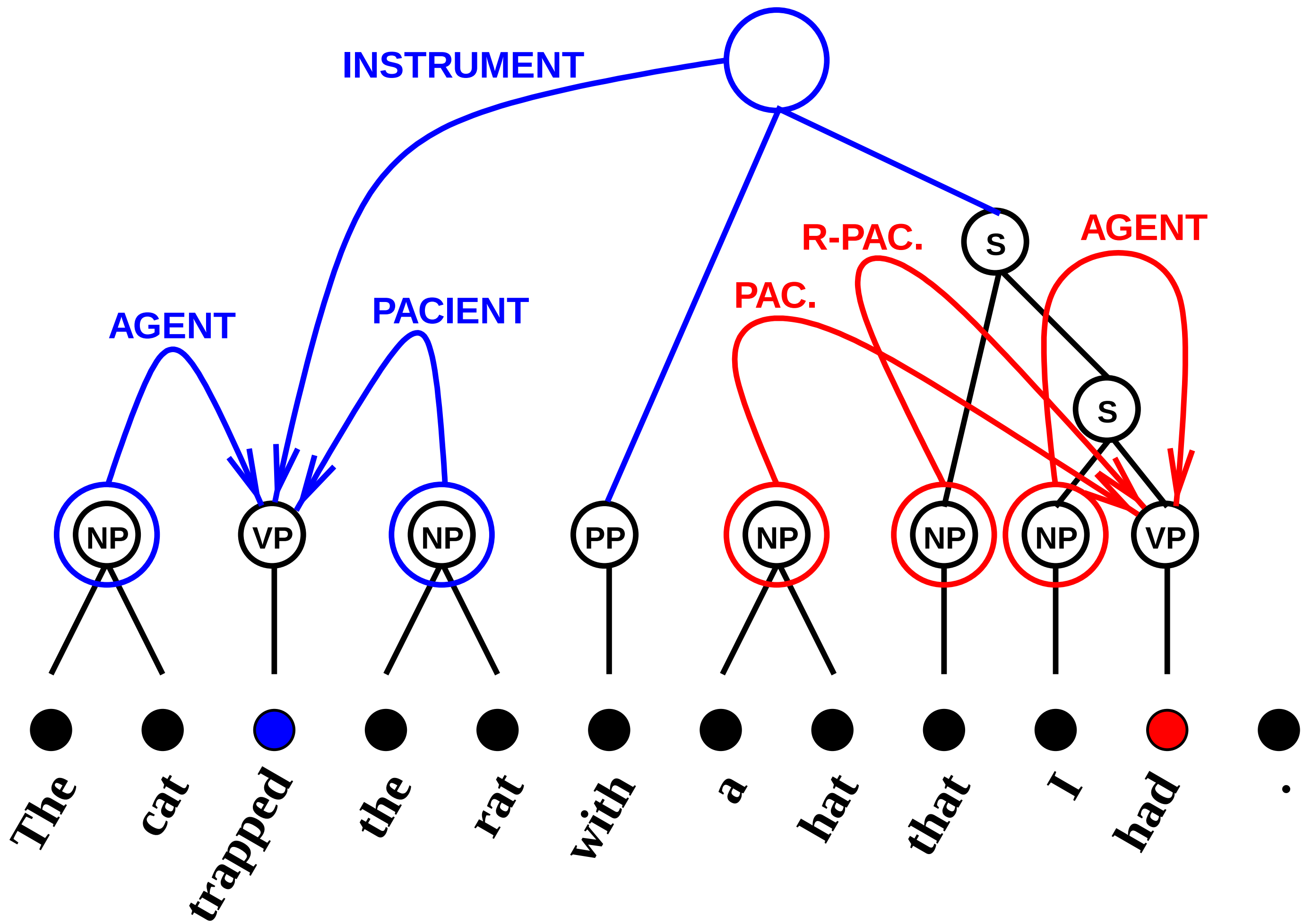


Semantic Role Labeling

- Phrase = Argument : a group of syntactic units playing a role with a predicate
- Example:
  `(The cat)`$_{\mathrm{AG}}$ `trapped (the rat)`$_{\mathrm{PAC}}$ `(with a hat)`$_{\mathrm{INS}}$
  - ⋆ For the predicate "trap":
    - ▷ AG is the agent (the entity that traps)
    - ▷ PAC is the pacient (the thing trapped)
    - ▷ INS is the instrument

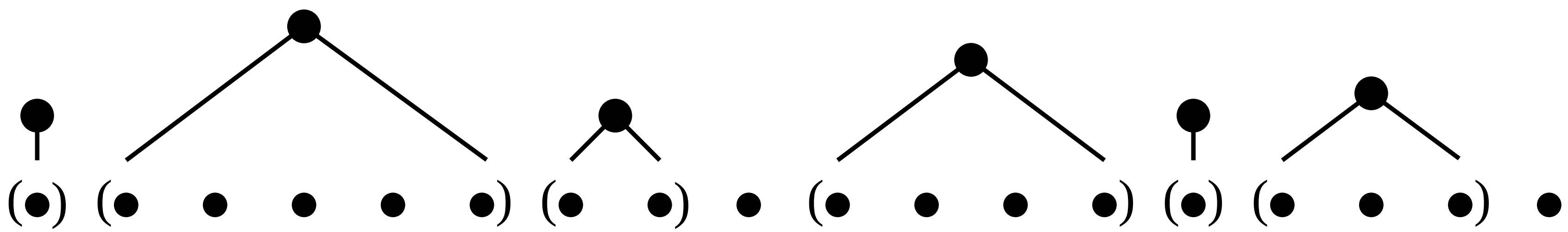
Phrase Recognition in Syntactic-Semantic Analysis



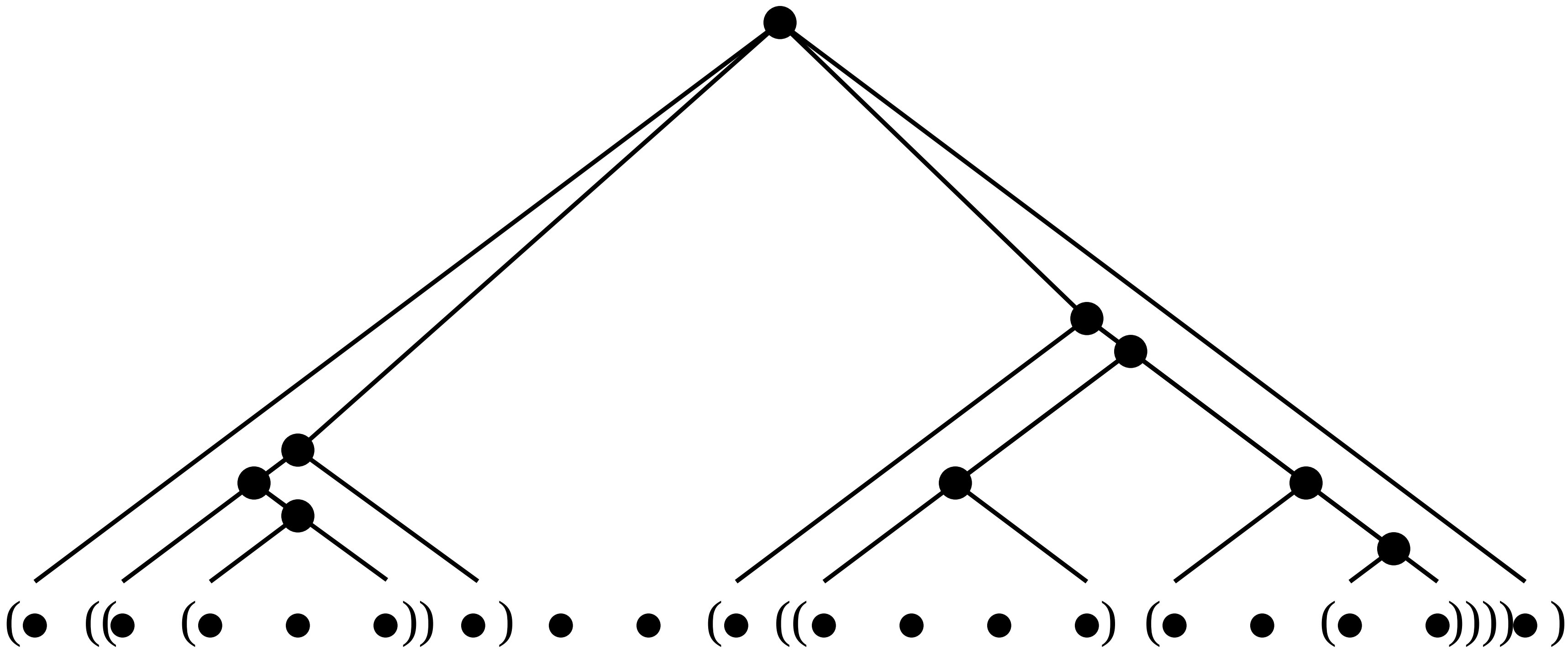
Phrase Recognition: general

- Goal: find phrases in a sentence, of types in $\mathcal{K}$
- Solution: a set of phrases, each of the form $(s, e)_k$, satisfying that:
  - ⋆ Phrases do not overlap (do not cross boundaries)
  - ⋆ Sequential Structures: phrases do not embed
  - ⋆ Hierarchical Structures: phrases may be embedded
- Evaluation: Precision/Recall/F_1 of recognized phrases

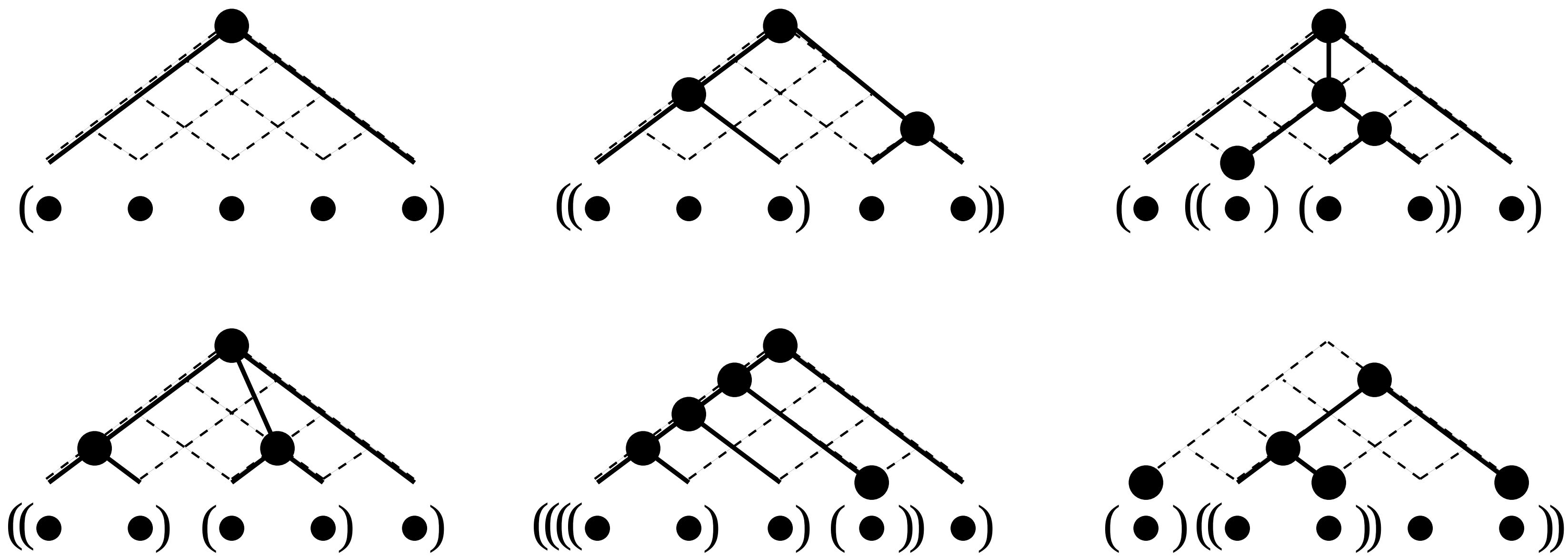
Sequential Phrase Structure: schematic view



Hierarchical Phrase Structure: schematic view

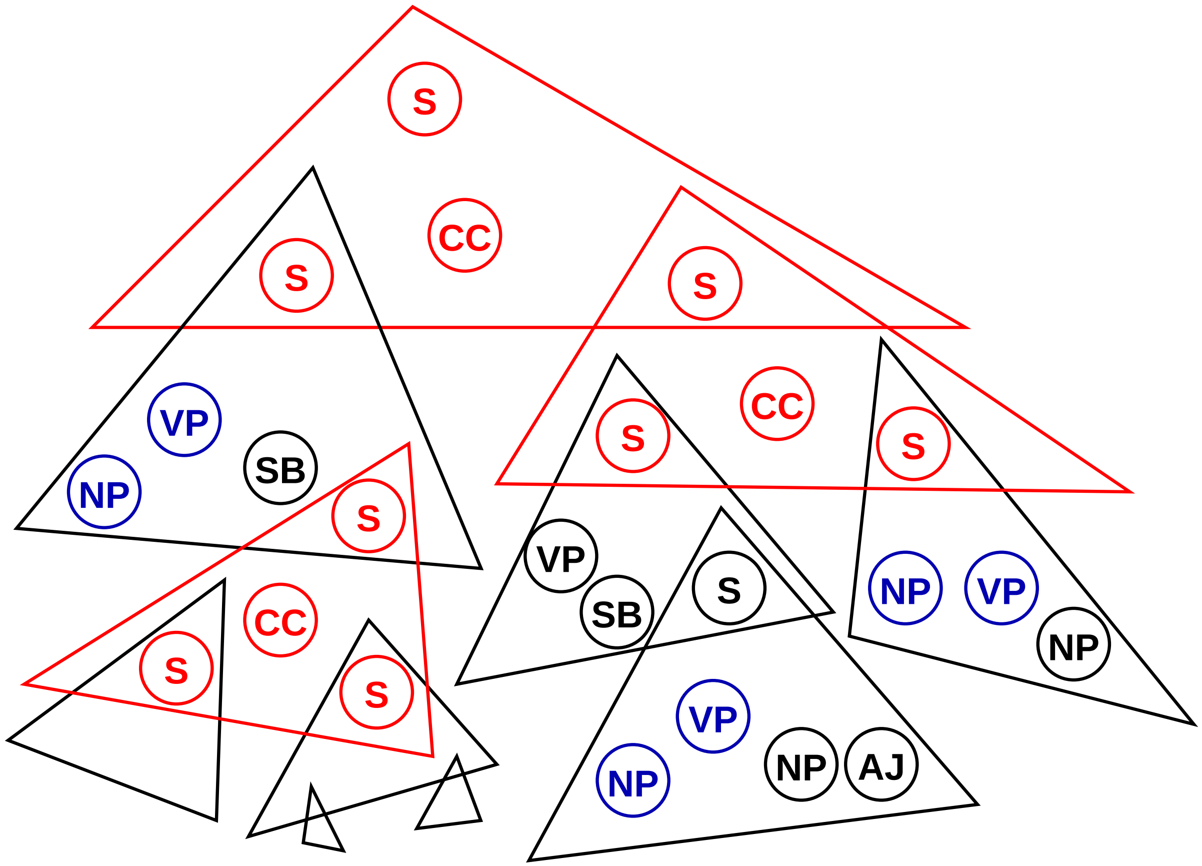


Observations (i): Huge Output Space



Output space is exponential: parsing strategy required

Observations (ii): Recursive Structures



Desirable to put learning in high-order level

This Thesis

- Proposes a general learning architecture for phrase recognition
- Presents state-of-the-art systems for several NL problems:
  - ⋆ Syntactic Chunking
  - ⋆ Clause Identification
  - ⋆ Semantic Role Labeling

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Supervised Machine Learning

- Given:
  - ⋆ A training set, with examples (x, y) where
    - ▷ $x \in \mathcal{X}$ could be sentences
    - ▷ $y \in \mathcal{Y}$ could be linguistic structures
    - ▷ We assume that the set was generated i.i.d. from an unknown distribution $\mathcal{D}$ over $\mathcal{X} \times \mathcal{Y}$
  - ⋆ An error function, or loss :
    $\mathrm{error}(y, \hat{y}) =$ cost of proposing $\hat{y}$ when the correct value was y
- Goal: learn a hypothesis

$$\mathrm{h} : \mathcal{X} \to \mathcal{Y}$$

that minimizes error on the entire distribution $\mathcal{D}$

Scenarios in Machine Learning

A general form of learning hypothesis:

$$\mathrm{h}(x) = \arg\max_{\hat{y} \in \mathcal{Y}} \mathrm{score}(x, \hat{y})$$

Depending on the output space $\mathcal{Y}$:

	Classes ($\mathcal{Y}$)	$\lvert\mathcal{Y}\rvert$	**enumeration of $\mathcal{Y}$**	**error**
Binary Classification	$\{+, -\}$	1	not needed	0-1
Multiclass Classification	A,B,C, . . .	m	exhaustive	0-1
Structure Learning	all structures	exponential	not tractable	prec/rec on nodes

Structure Learning: Learning & Inference

- $\mathcal{Y}(x)$ is exponential on the size of x
- Not possible to exhaustively enumerate the output space
- Learning & Inference approach:
  - ⋆ Key Idea: decompose a structure into fragments
  - ⋆ Model: scores a structure by scoring its fragments
  - ⋆ Inference: search in $\mathcal{Y}(x)$ for the best scored solution for x
    - ▷ Build incrementally, instead of explore exhaustively
    - ▷ Use automata, grammars, . . . to build the solution
    - ▷ Use constraints to discard regions of $\mathcal{Y}(x)$

Generative Learning (i): Models

- Probabilistic models that define a joint probability distribution of the data
- The model is associated to a stochastic generation mechanism of the data, such as an automaton or grammar
- Paradigmatic models to recognize structure:
  - ⋆ Hidden Markov Models, e.g. **[Rabiner 89]**
  - ⋆ Probabilistic Context-Free Grammars, e.g. **[Collins 99]**

Generative Learning (ii): Max-Likelihood Estimation

- Based on theory of probability and Bayesian learning:
  - ⋆ Training: via Maximum Likelihood, i.e., counts on training
  - ⋆ Inference Algorithms: e.g., Viterbi, CKY, etc.

- But:
  - ⋆ Difficult to use arbitrary representations
    - ▷ Features are tied to the generation mechanism of the data
    - ▷ Otherwise, the training process becomes too complex
  - ⋆ Asymptotic convergence wrt. the size of training data

Direct, Discriminative Learning

- ML methods that directly model the mapping between $\mathcal{X}$ and $\mathcal{Y}$
- Allow arbitrary representations
- Not necessarily probabilistic
- Mostly designed for classification, mostly binary
- A wide range of methods appeared in the AI community during the 80's and 90's:
  - ⋆ Maximum Entropy
  - ⋆ Decision Trees (or Lists)
  - ⋆ Memory-based
  - ⋆ Transformation-based
  - ⋆ Neural Nets, Perceptron
  - ⋆ AdaBoost
  - ⋆ Support Vector Machines
  - ⋆ . . .

Learning and Inference: General Approach

- Transform the recognition problem into a chain of *simple* decisions:
  - ⋆ Segmentation Decisions:
    e.g., Open-Close, Begin-Inside-Outside, Shift-Reduce, etc.
  - ⋆ Labeling Decisions: made during segmentation or afterwards
  - ⋆ Decisions might use the output of earlier steps in the chain
- Set up an inference strategy:
  - ⋆ Decisions are applied in chain to build structure incrementally
  - ⋆ Exploration might be at different levels of amplitude:
    e.g., greedy, dynamic programming, beam search, etc.
- Learn a prediction function for each decision

Learning & Inference: Local vs. Global Training

- Local training: each local function is trained separately, as a classifier (binary or multiclass)
  - ⋆ Good understanding on learning classifiers
  - ⋆ *but* local accuracies do not guarantee global accuracy
  - ⋆ *that is*, a local classification behavior might not be the optimal within inference
  - ⋆ *unless* local classifications are perfect

- Global training: train the recognizer as a composed function
  - ⋆ Local functions are trained dependently to optimize global accuracy
  - ⋆ e.g., Linear models **[Collins 02,04]**, CRFs **[Lafferty et al. 01]**

Learning Linear Separators (i)

- Most learning algorithms look for linear separators, under different criteria **[Roth 98,99][Collins 02]**
- Properties: simple, expressive, efficient
- Flexible at learning different prediction policies
- A linear separator has the following form:

$$\mathrm{score}(x, y) = \mathbf{w} \cdot \phi(x, y)$$

where:

⋆ ϕ is a feature extraction function, given *a priori*

⋆ $\mathbf{w}$ is a weight vector, learned by the algorithm

Learning Linear Separators (ii): Separability

- Recent theoretical work concentrates on learning linear separators
- Separability: ability to separate between correct/incorrect instances
- **[Vapnik 95]**:
  - ⋆ large separation on training $\Longrightarrow$ low generalization error
  - ⋆ A quantity called margin measures how much a hypothesis separates between correct/incorrect instances
  - ⋆ Margin-based algorithms: look for linear separators that . . .
    - ▷ Perceptron: achieve positive margins
    - ▷ Support Vector Machines: achieve maximum margins

Learning Linear Separators (iii): Perceptron

- Online algorithm, with additive mistake-driven updates:
  - ⋆ Promotion, when a prediction is too low (controls recall)
  - ⋆ Demotion, when a prediction is too high (controls precision)
- With appropiate definitions of margin, can be used for:
  - ⋆ binary classifiers **[Rosenblatt 58]**
  - ⋆ multiclass **[Crammer & Singer 03]**
  - ⋆ ranking functions **[Collins 02]**
- Extensions: Voted Perceptron **[Freund & Schapire 99]**
  - ⋆ Voting techniques to obtain larger margins
  - ⋆ Kernel method: polynomial functions, structure kernels, . . .

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Filtering-Ranking Architecture

- A general architecture to recognize phrase structures
- Two levels of learning:
  - ⋆ Filter: decides which words start/end a phrase
  - ⋆ Ranker: scores phrases
- On the top, dynamic programming inference builds the best-scored phrase structure
- We propose FR-Perceptron: a Perceptron learning algorithm tailored for the architecture

Filtering-Ranking Architecture: Decomposition

- A solution is decomposed at phrase level:

$$\mathrm{score}(x, y) = \sum_{(s,e)_k \in y} \mathrm{score}_{\mathrm{p}}(x, y, (s, e)_k)$$

- Still, the number of phrases grows quadratically with the sentence length

- We reduce the space of phrases by filtering at word level.
For a phrase $(s, e)_k$ to be in a solution:

$$\mathrm{start}_{\mathrm{w}}(x, s, k) > 0 \quad \wedge \quad \mathrm{end}_{\mathrm{w}}(x, e, k) > 0$$

Filtering-Ranking Model

$\mathcal{Y}$: solution space, i.e. set of all phrase structures

$\mathcal{Y}_{\mathrm{SE}}$: practical solution space, filtered at word level:

$$\mathcal{Y}_{\mathrm{SE}} = \{ y \in \mathcal{Y} \mid \forall (s,e)_k \in y \;\; \mathrm{start_w}(x,s,k) \wedge \mathrm{end_w}(x,e,k) \}$$

The Filtering-Ranking architecture computes:

$$\mathrm{R}(x) = \arg\max_{y \in \mathcal{Y}_{\mathrm{SE}}} \sum_{(s,e)_k \in y} \mathrm{score_p}(x, y, (s,e)_k)$$

using dynamic-programming.

Filtering-Ranking Strategy

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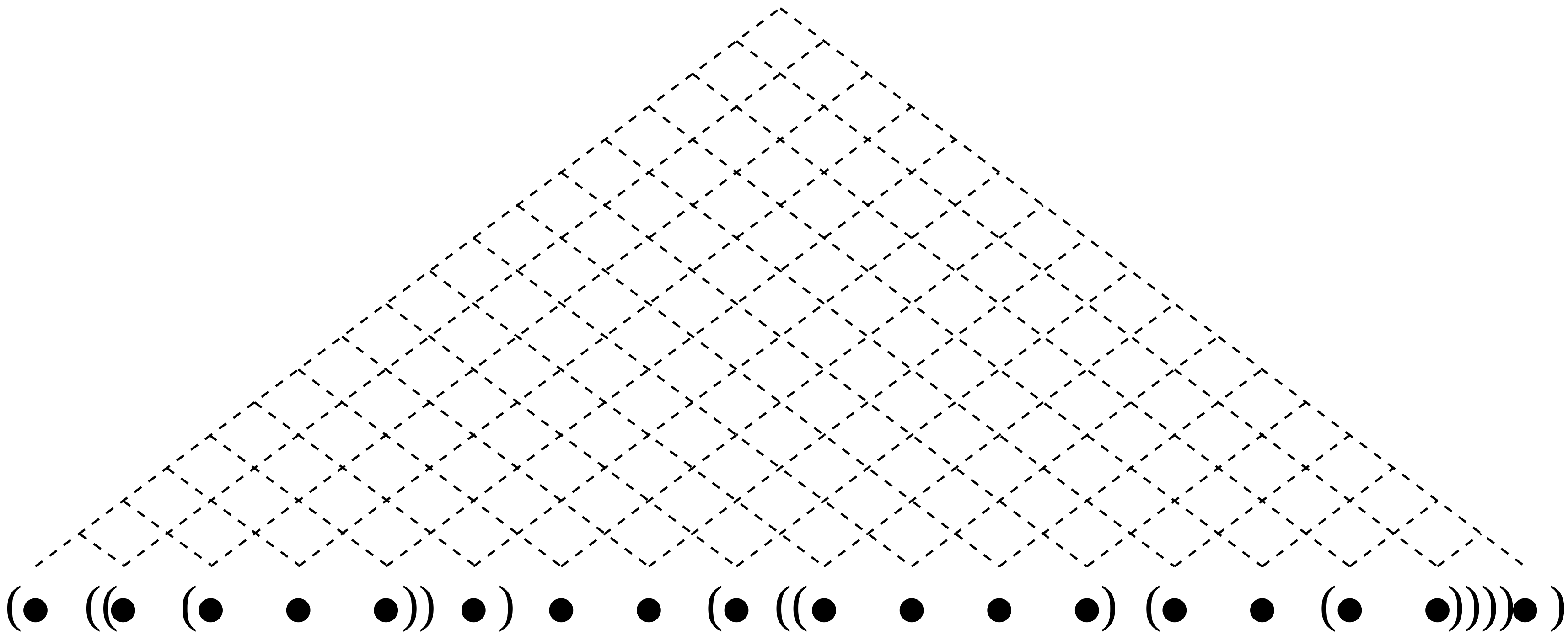
Filtering-Ranking Strategy



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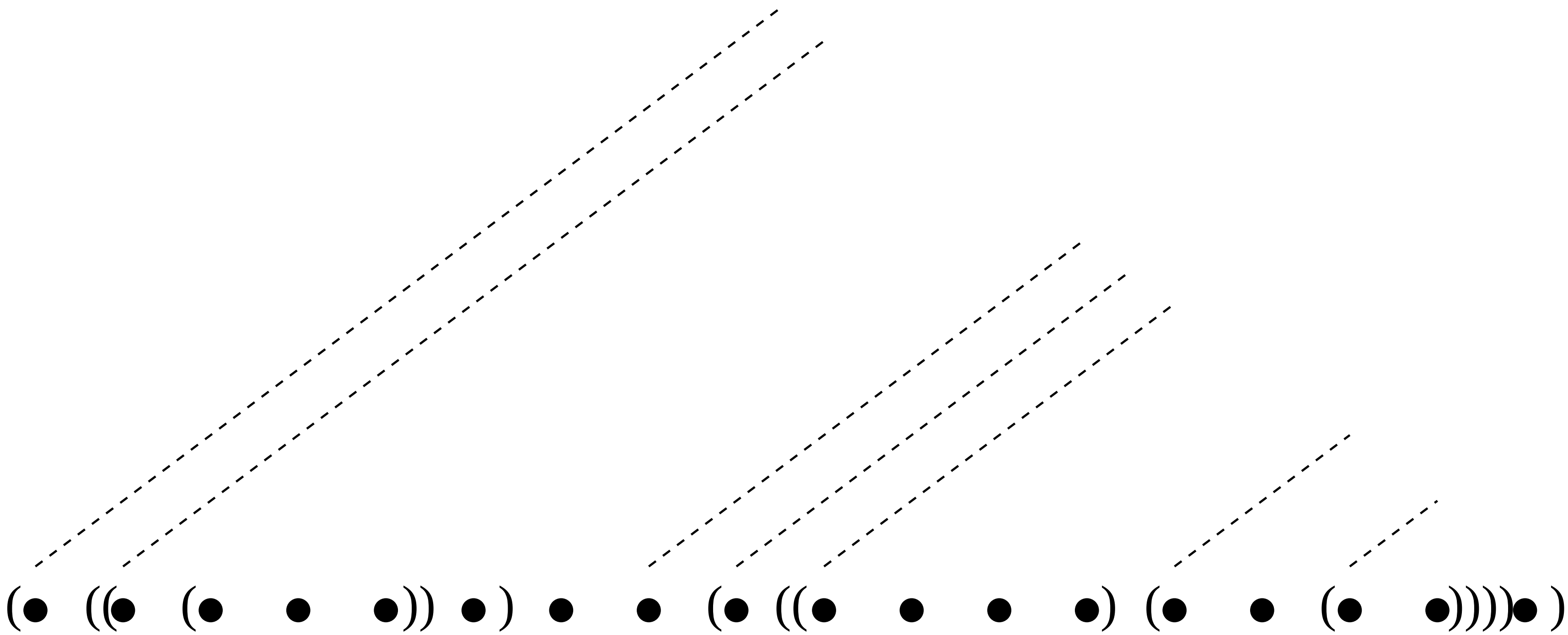

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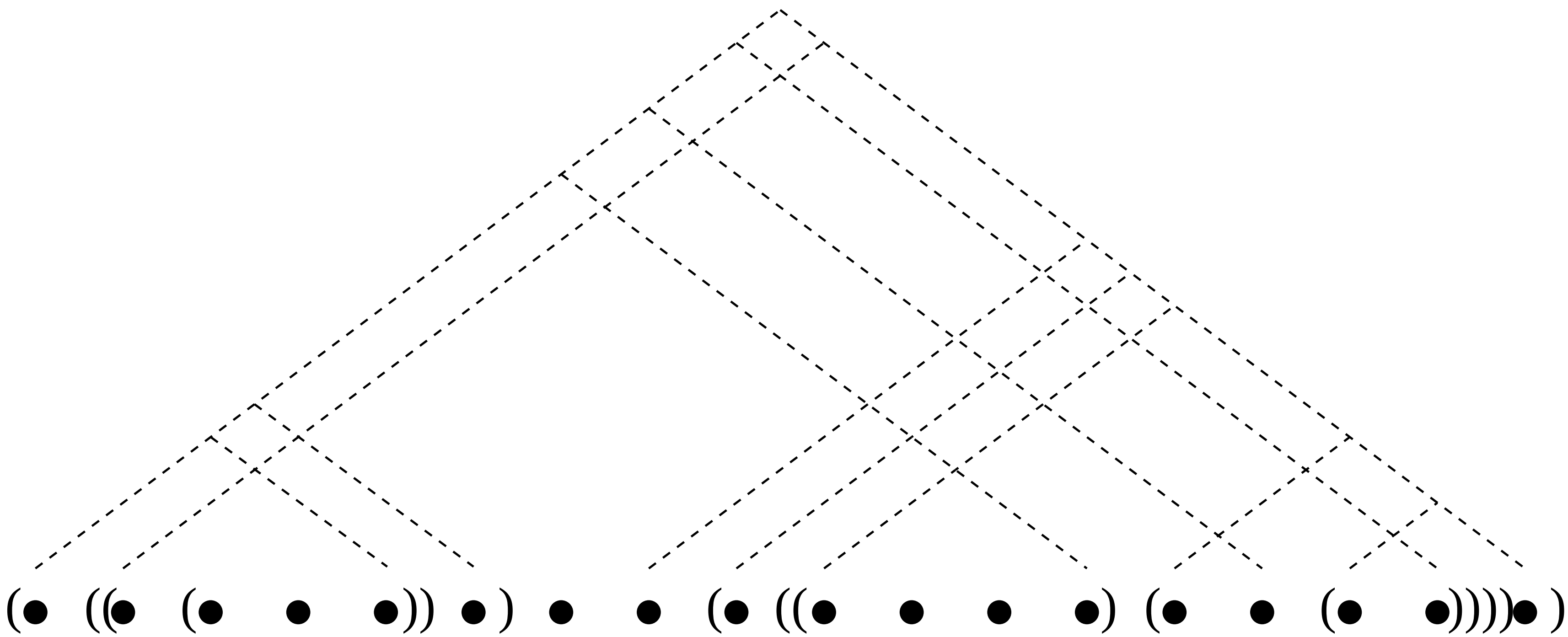

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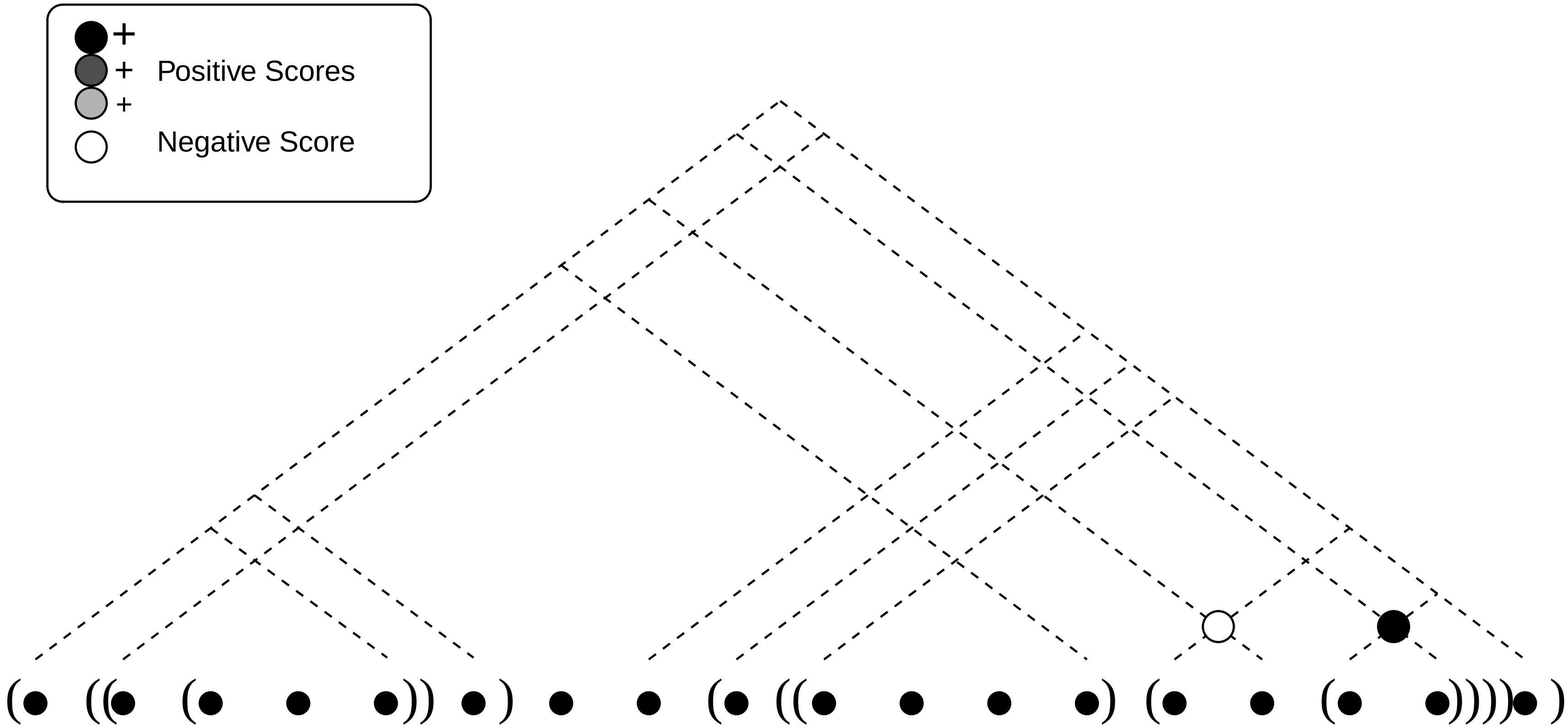

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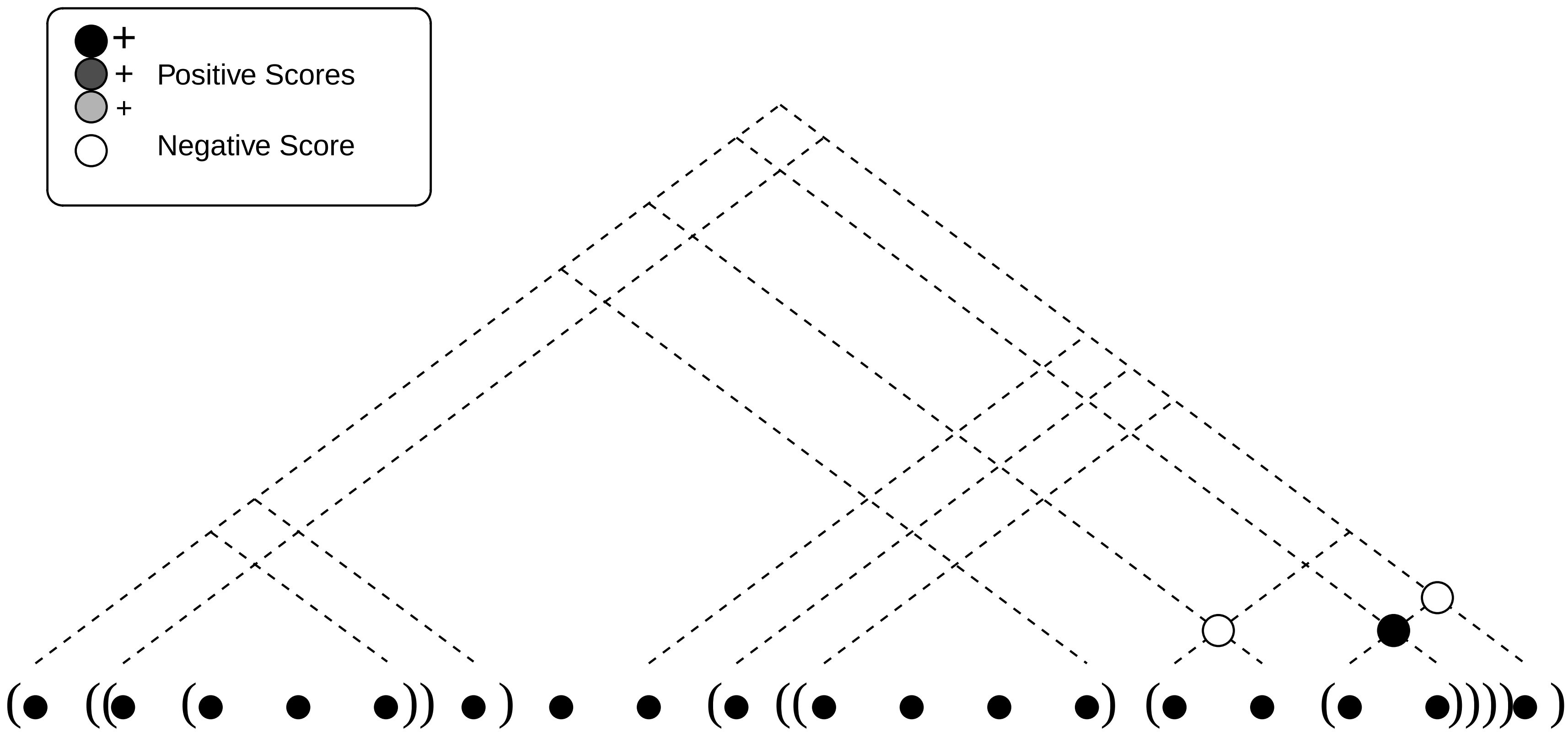

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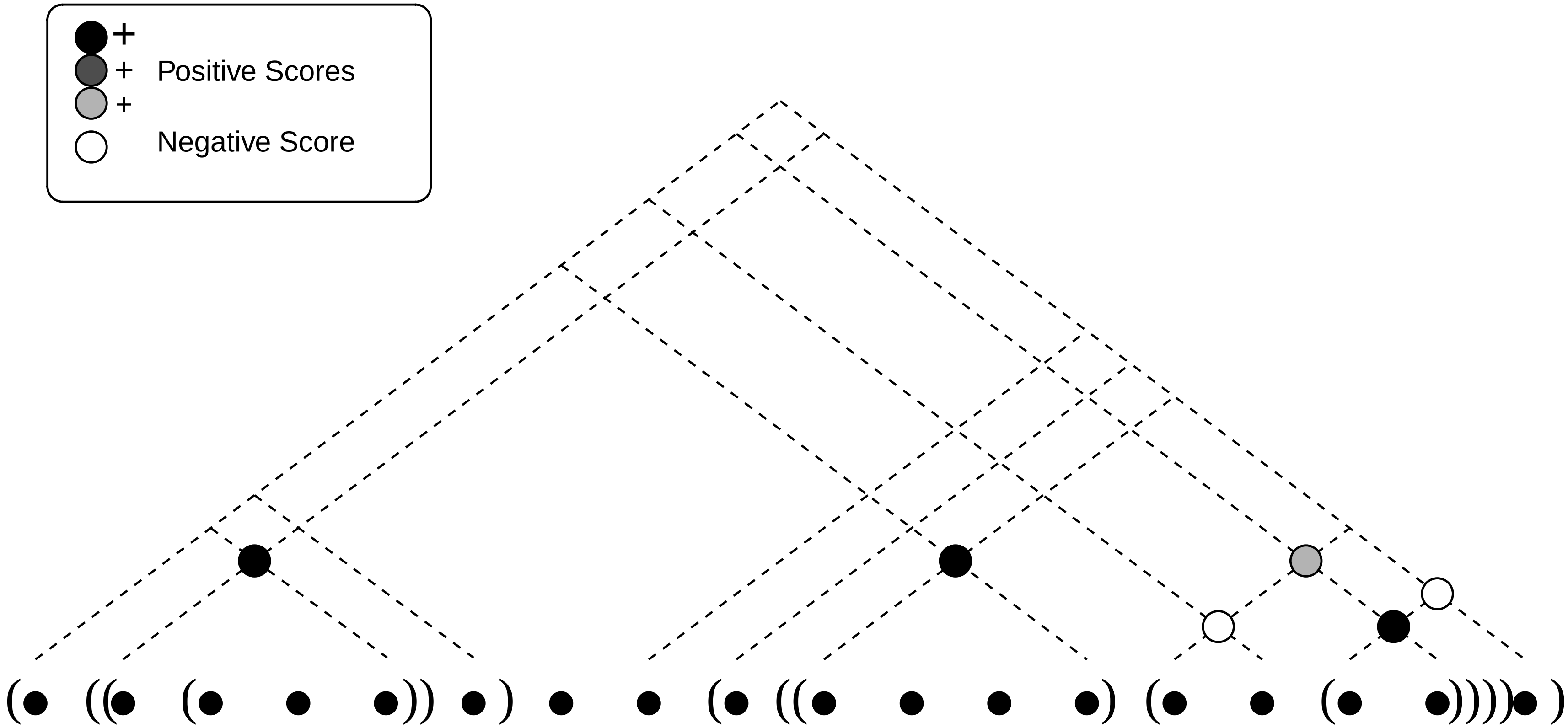

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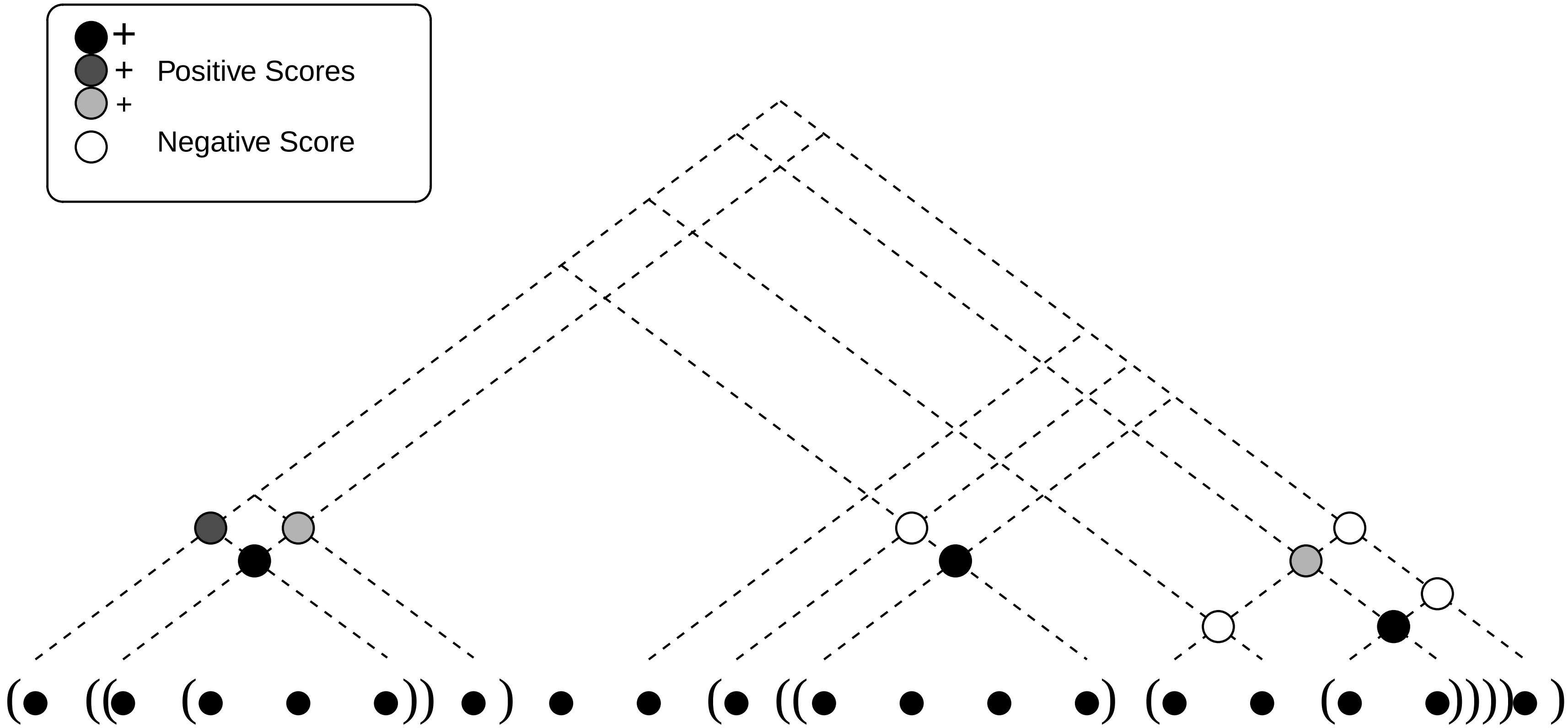

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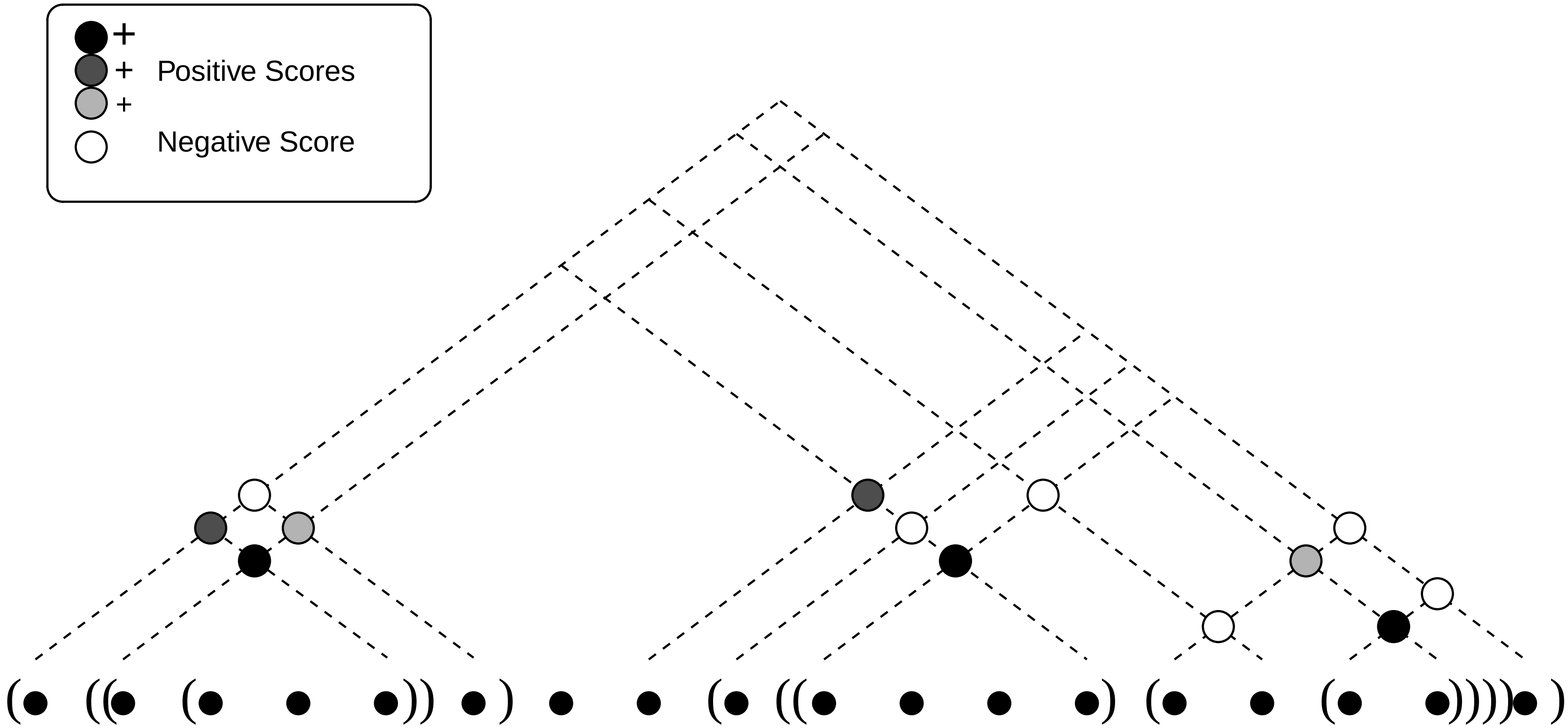

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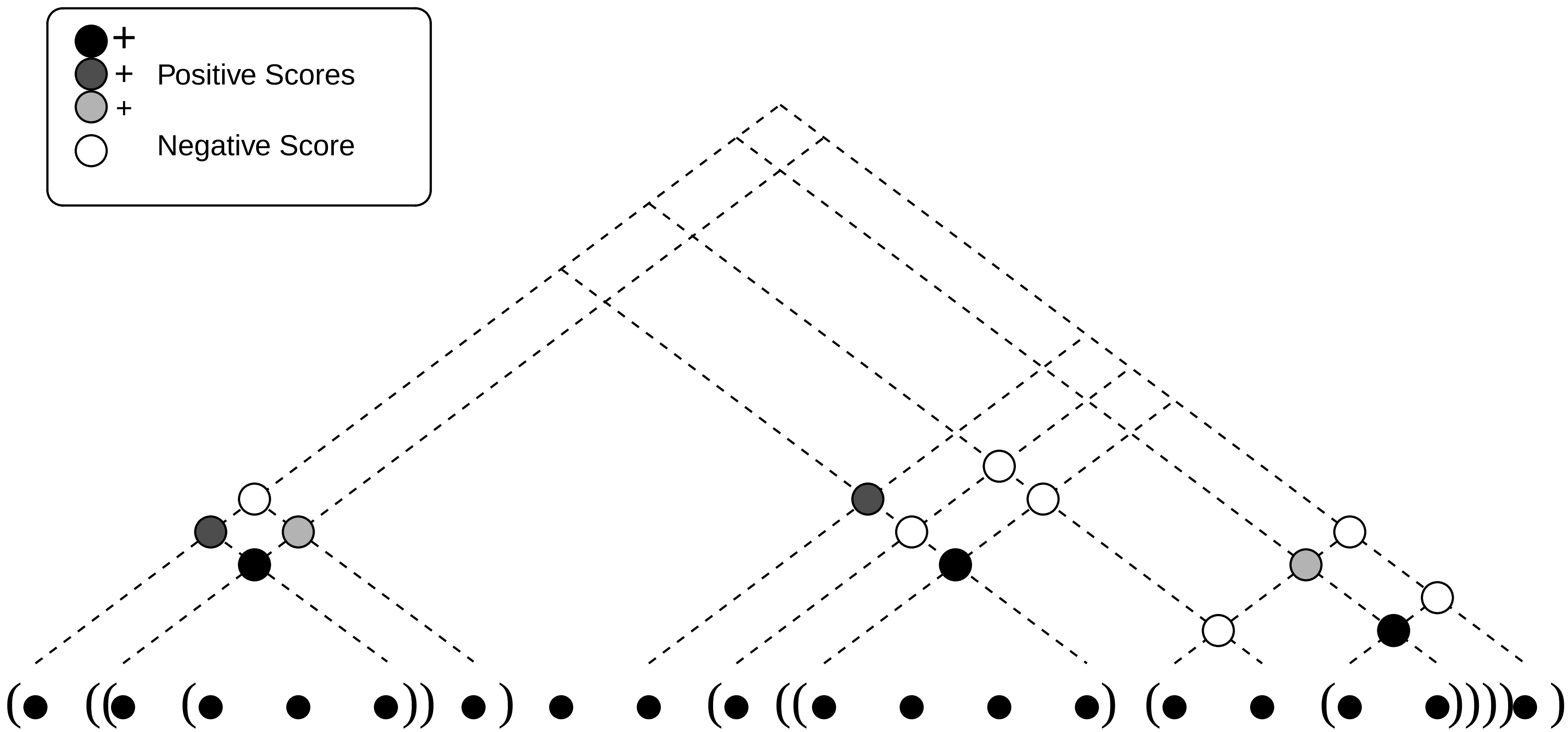

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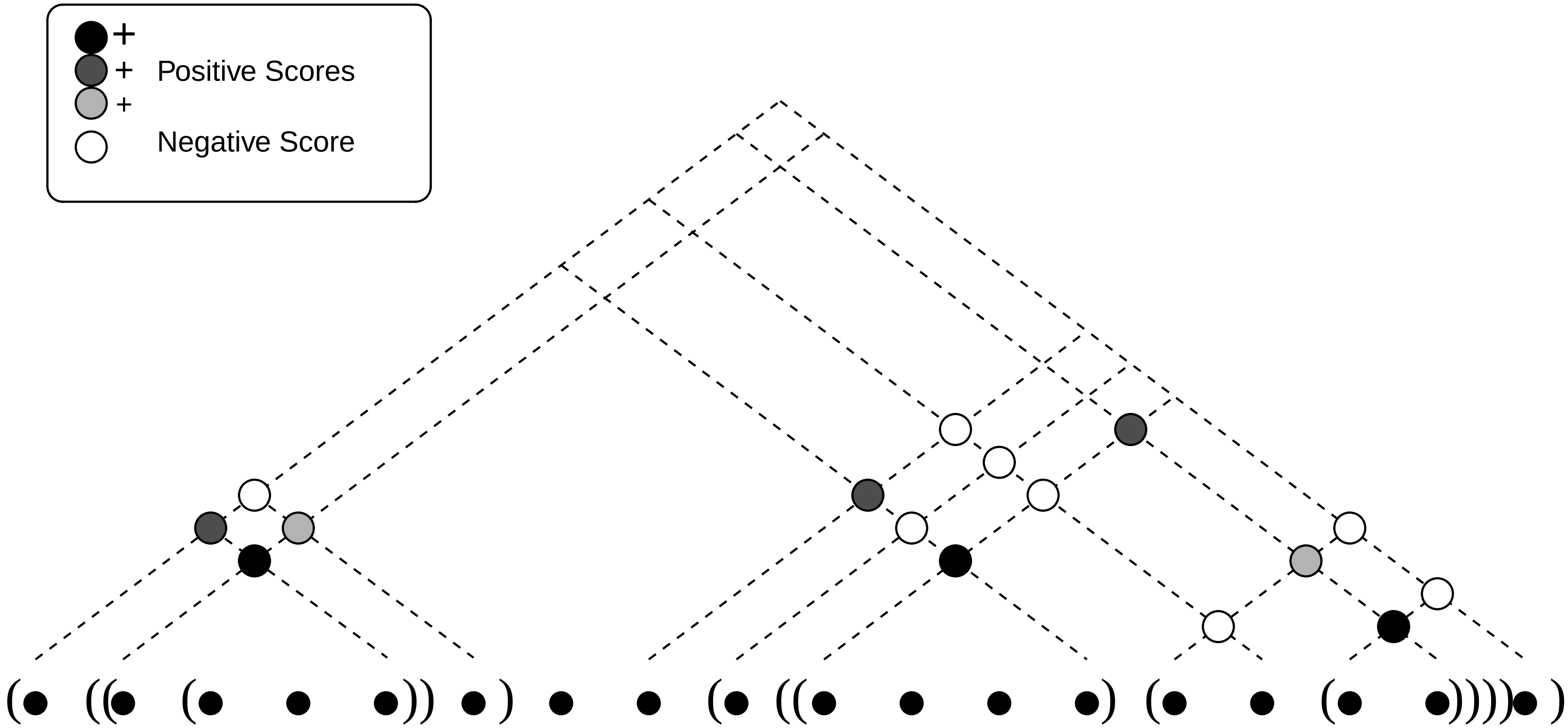

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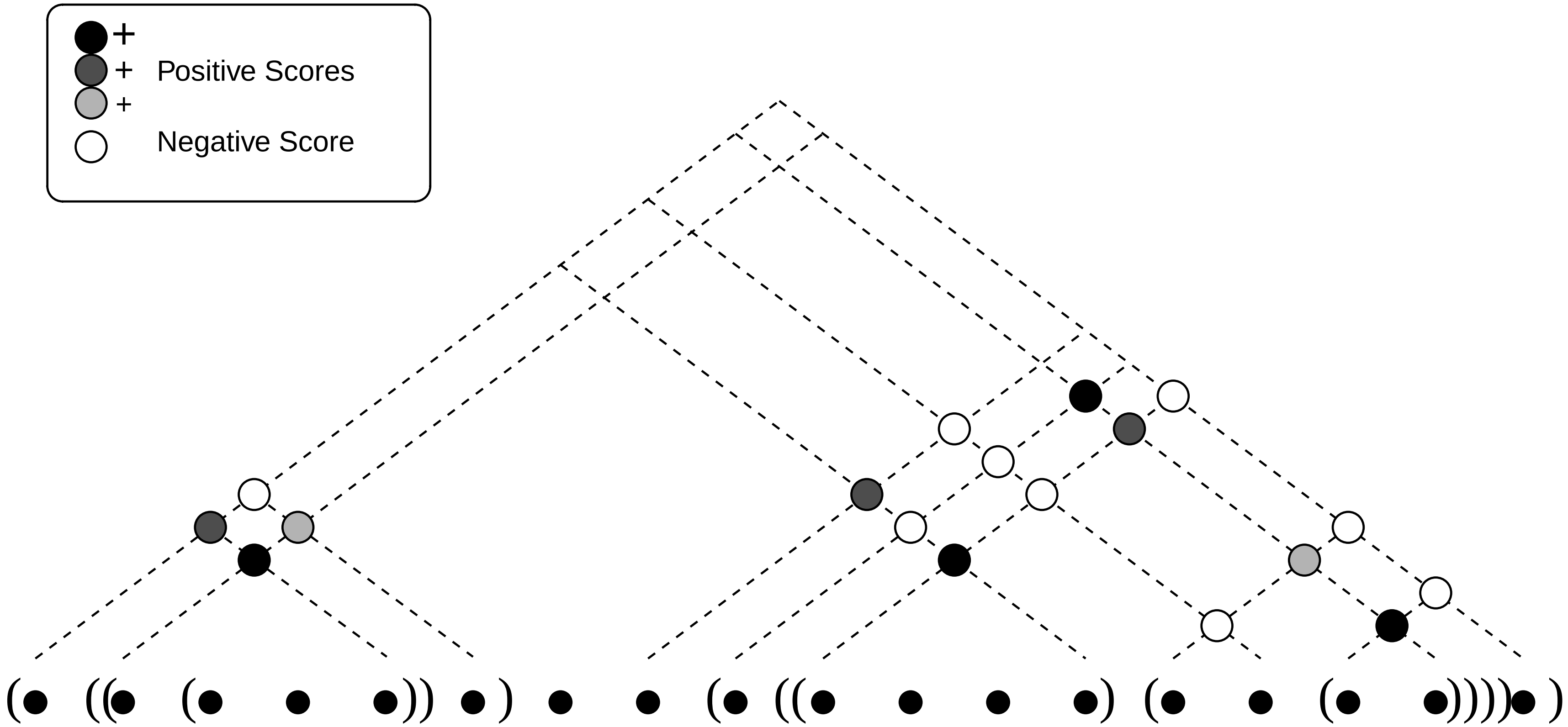

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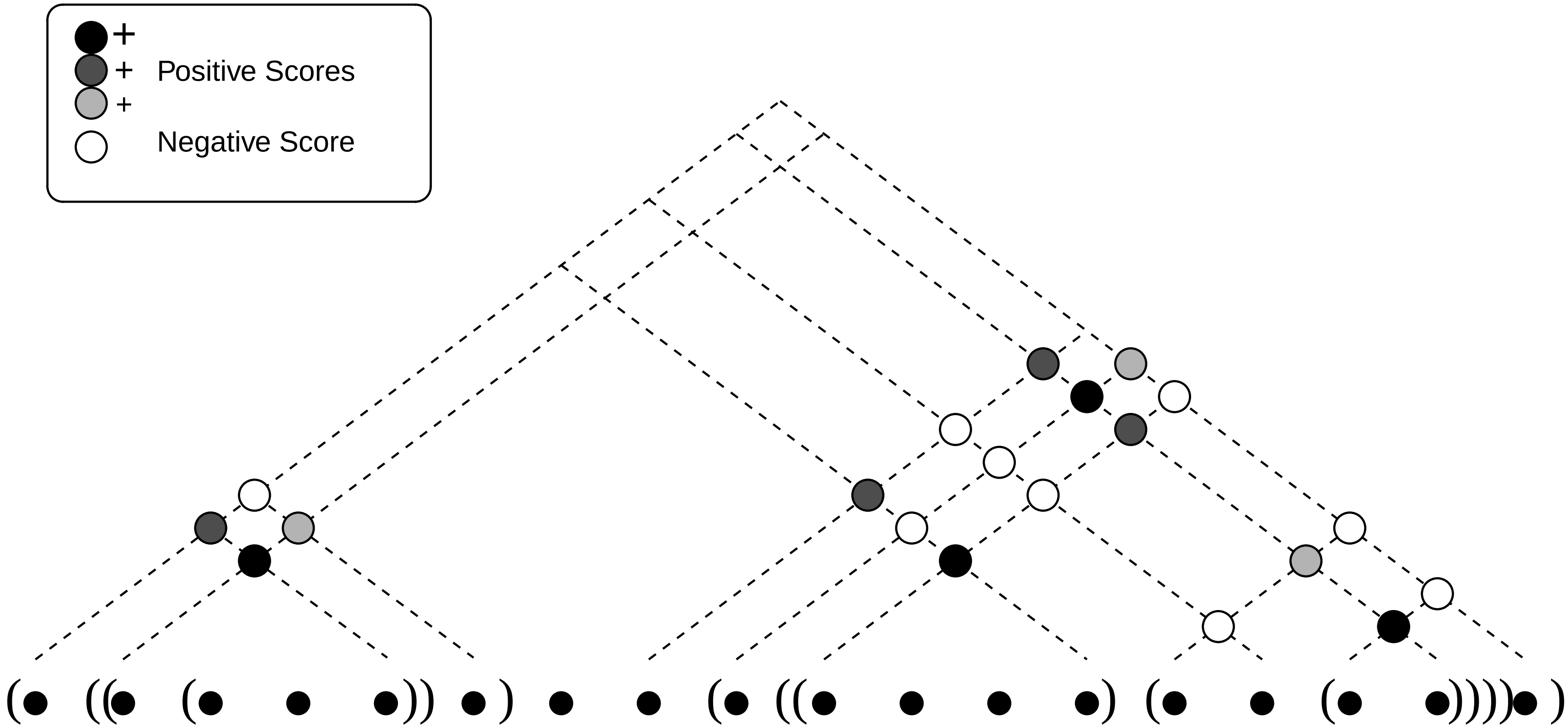

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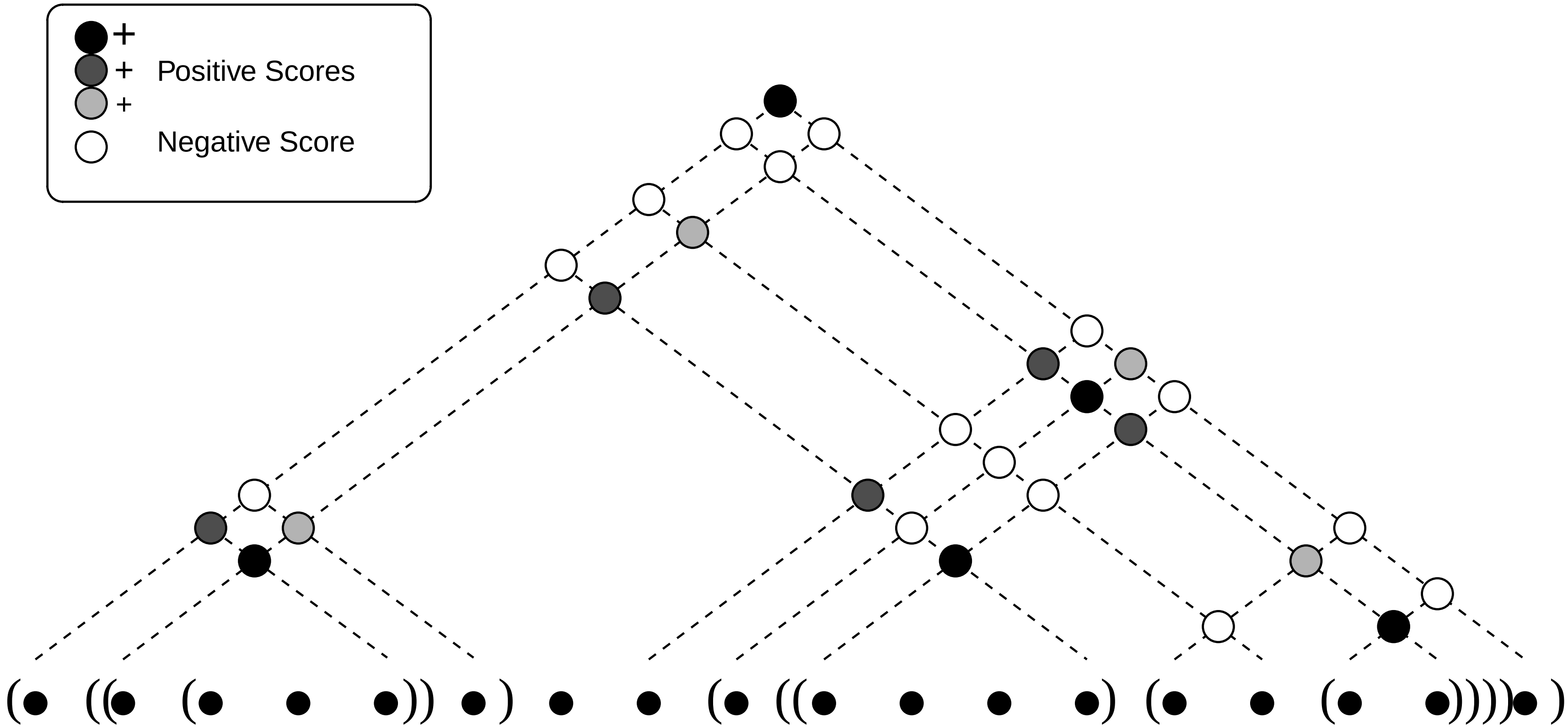

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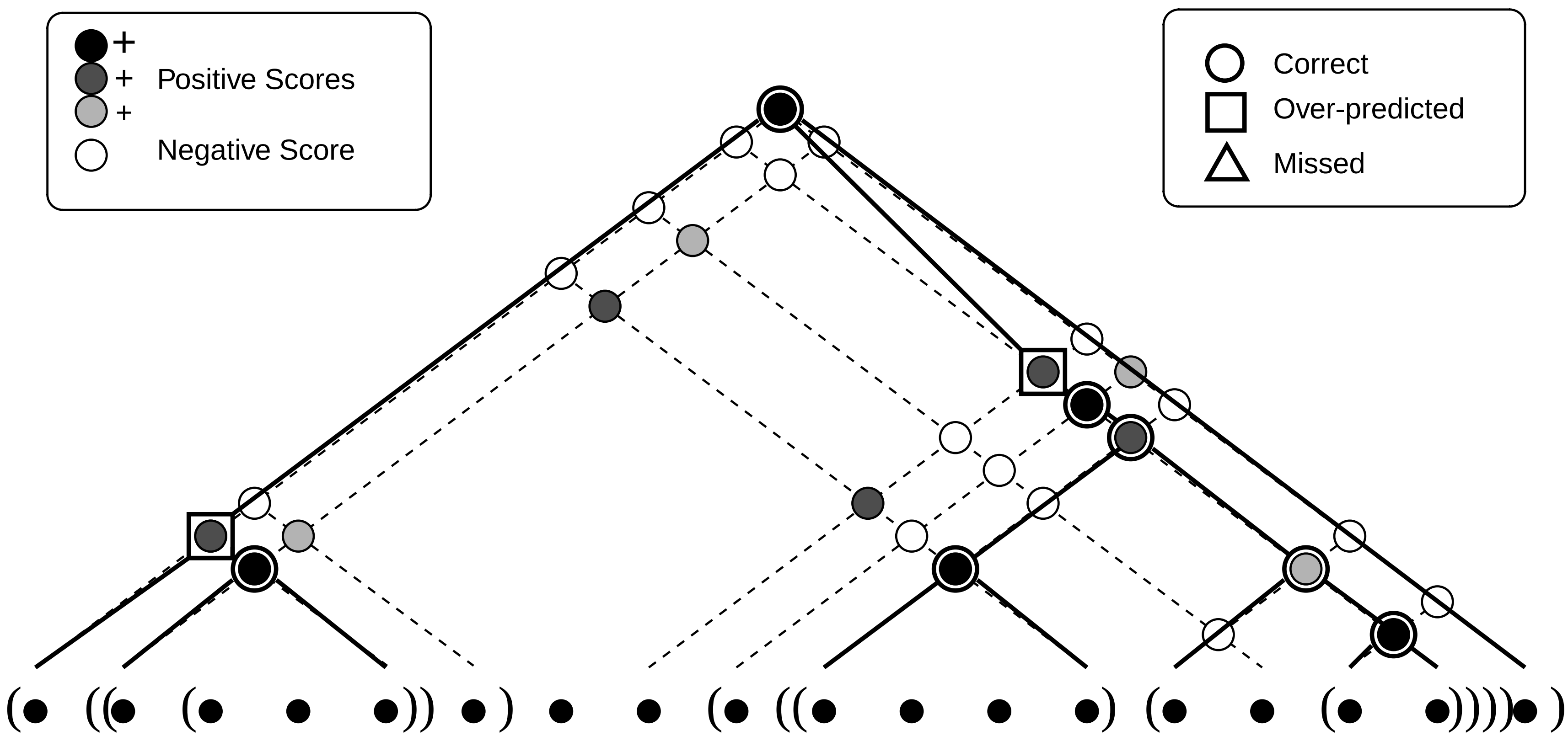

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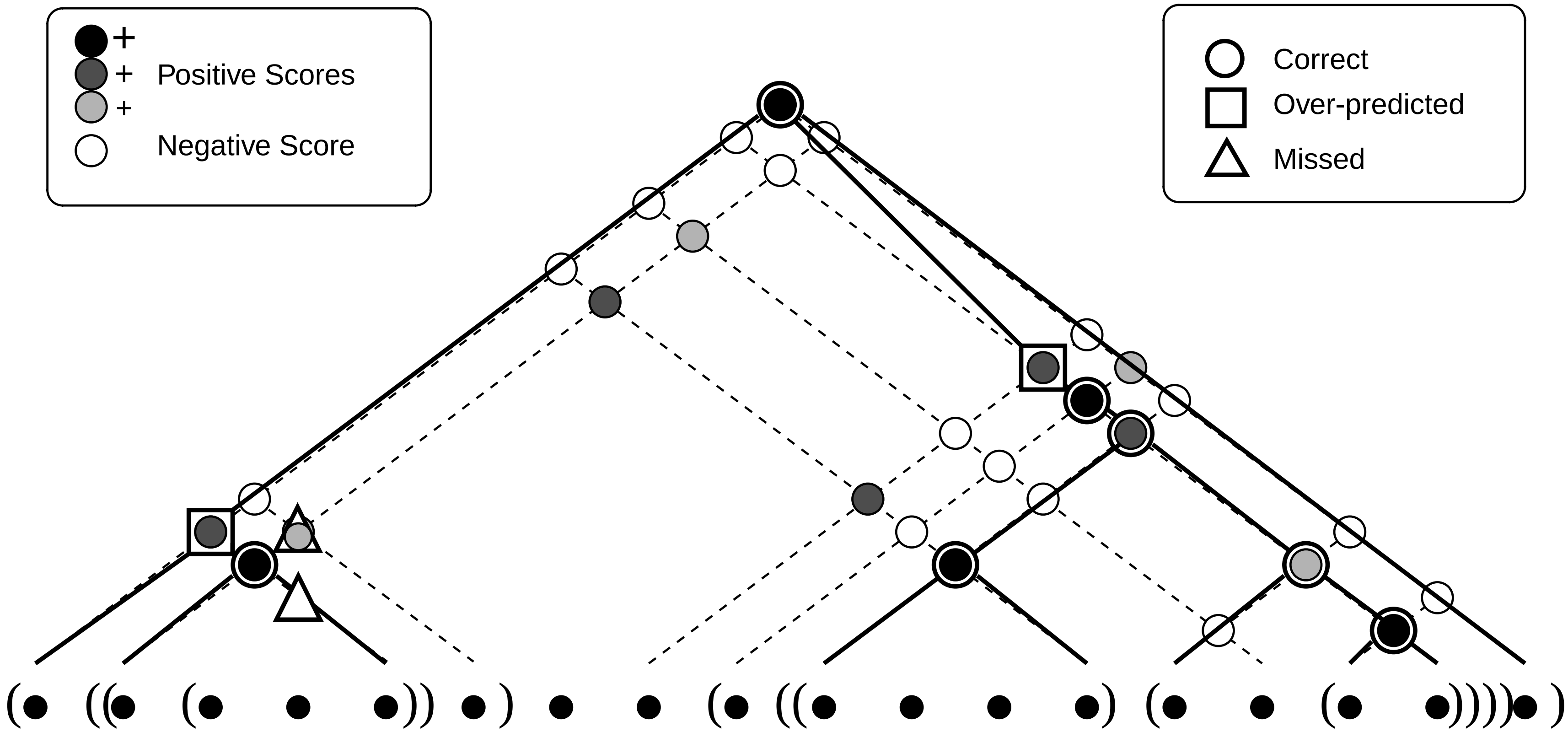


Learning a Filtering-Ranking Model

- Goal: Learn the functions $(\mathrm{start_w}, \mathrm{end_w}, \mathrm{score_p})$ so as to maximize the F_1 measure on the recognition of phrases

- Desired behavior:
  - ⋆ Start-End Filters:
    - ▷ Do not block any correct phrase: very high recall
    - ▷ Block phrases that produce errors at the ranking stage
    - ▷ Block much incorrect phrases as possible
  - ⋆ Ranker:
    - ▷ Separate between correct/incorrect structures
    - ▷ Forget about filtered phrases

Perceptron Learning at Global Level

- Following **[Collins 02]**, we guide learning at global level:
  - ⋆ Do not concentrate on individual errors of the learning functions
  - ⋆ Instead, concentrate on errors at sentence level, after inference
- Key points:
  - ⋆ Mistake-driven learning, a.k.a. Perceptron
  - ⋆ Functions are learned together, visiting online training sentences
  - ⋆ Errors are propagated from sentence-level, to phrase-level, to word-level

Filtering-Ranking Perceptron

- Configuration:
  - ⋆ Feature extraction functions (given): ϕ_{w}, ϕ_{p}
  - ⋆ Weight vectors (learned): $\mathbf{w}_{\mathrm{S}}$, $\mathbf{w}_{\mathrm{E}}$, $\mathbf{w}_{\mathrm{p}}$

- Algorithm: visit online sentence-structure pairs (x, y):
  1. Infer the best phrase structure $\hat{y}$ for x
  2. Identify errors and provide feedback to weight vectors.
     We consider only errors at global level, comparing y and $\hat{y}$:
     - ⋆ Missed Phrases (those in $y \setminus \hat{y}$)
     - ⋆ Over-predicted Phrases (those in $\hat{y} \setminus y$)

FR-Perceptron: Feedback on Missed phrases

If a phrase $(s,e)_k$ is missed, do promotion updates:

- if word s is not positive start for k:
  $$\mathbf{w}_{\mathrm{S}} = \mathbf{w}_{\mathrm{S}} + \phi_{\mathrm{w}}(x,s,k)$$
- if word e is not positive end for k:
  $$\mathbf{w}_{\mathrm{E}} = \mathbf{w}_{\mathrm{E}} + \phi_{\mathrm{w}}(x,e,k)$$
- if $(s,e)_k$ passes the filter (s/e are positive start/end for k):
  $$\mathbf{w}_{\mathrm{p}} = \mathbf{w}_{\mathrm{p}} + \phi_{\mathrm{p}}(x,y,(s,e)_k)$$

FR-Perceptron: Feedback on Over-Predicted phrases

If a phrase $(s, e)_k$ is over-predicted, do demotion updates:

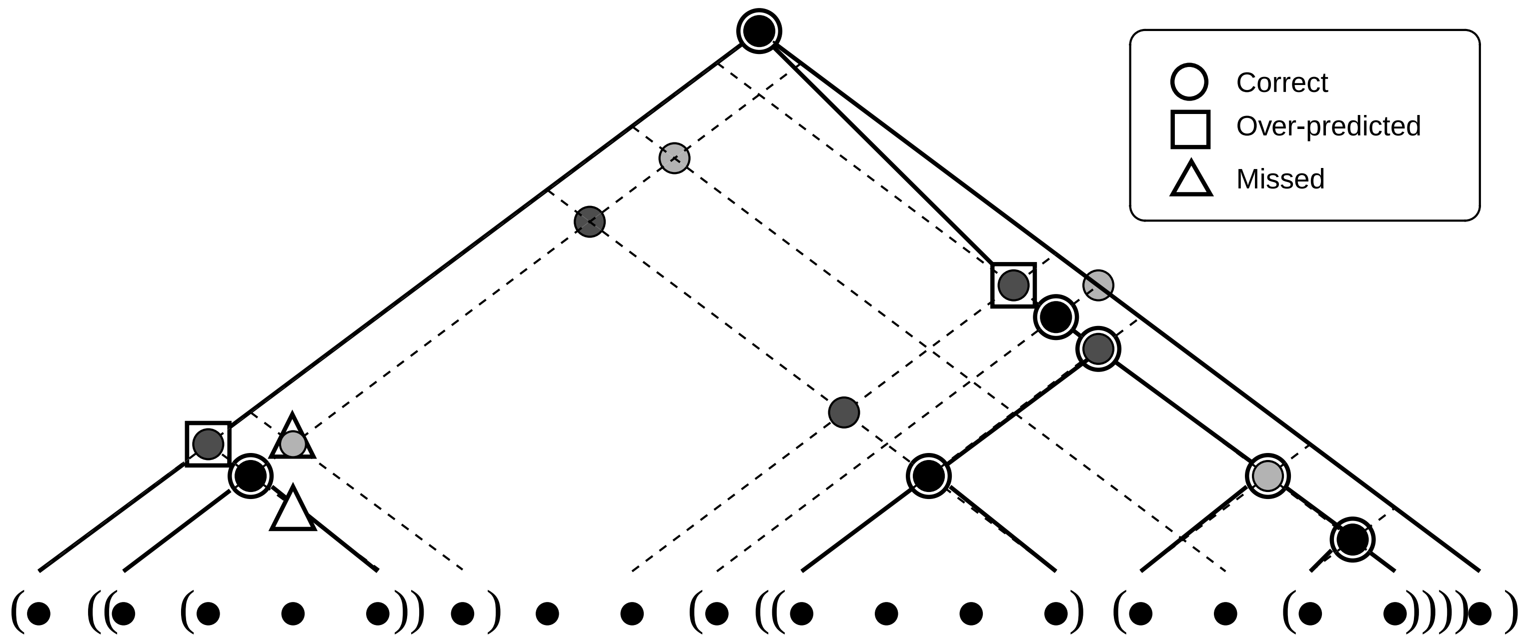
- Give feedback to the ranker:
$$\mathbf{w}_{\mathrm{p}} = \mathbf{w}_{\mathrm{p}} - \phi_{\mathrm{p}}(x, y, (s, e)_k)$$

- If word s is not a correct start for k:
$$\mathbf{w}_{\mathrm{S}} = \mathbf{w}_{\mathrm{S}} - \phi_{\mathrm{w}}(x, s, k)$$

- If word e is not a correct end for k:
$$\mathbf{w}_{\mathrm{E}} = \mathbf{w}_{\mathrm{E}} - \phi_{\mathrm{w}}(x, e, k)$$

Learning Feedback: Example

- Local predictions are **corrected** wrt. the global solution



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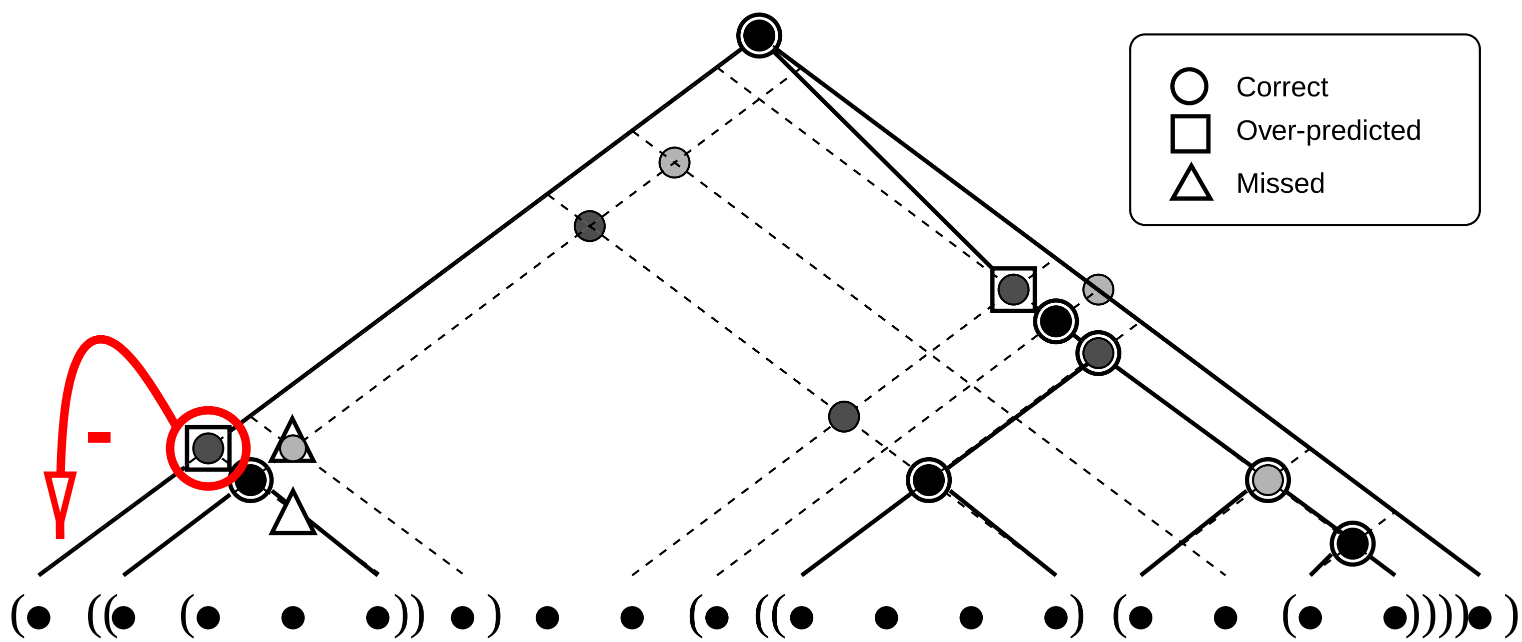

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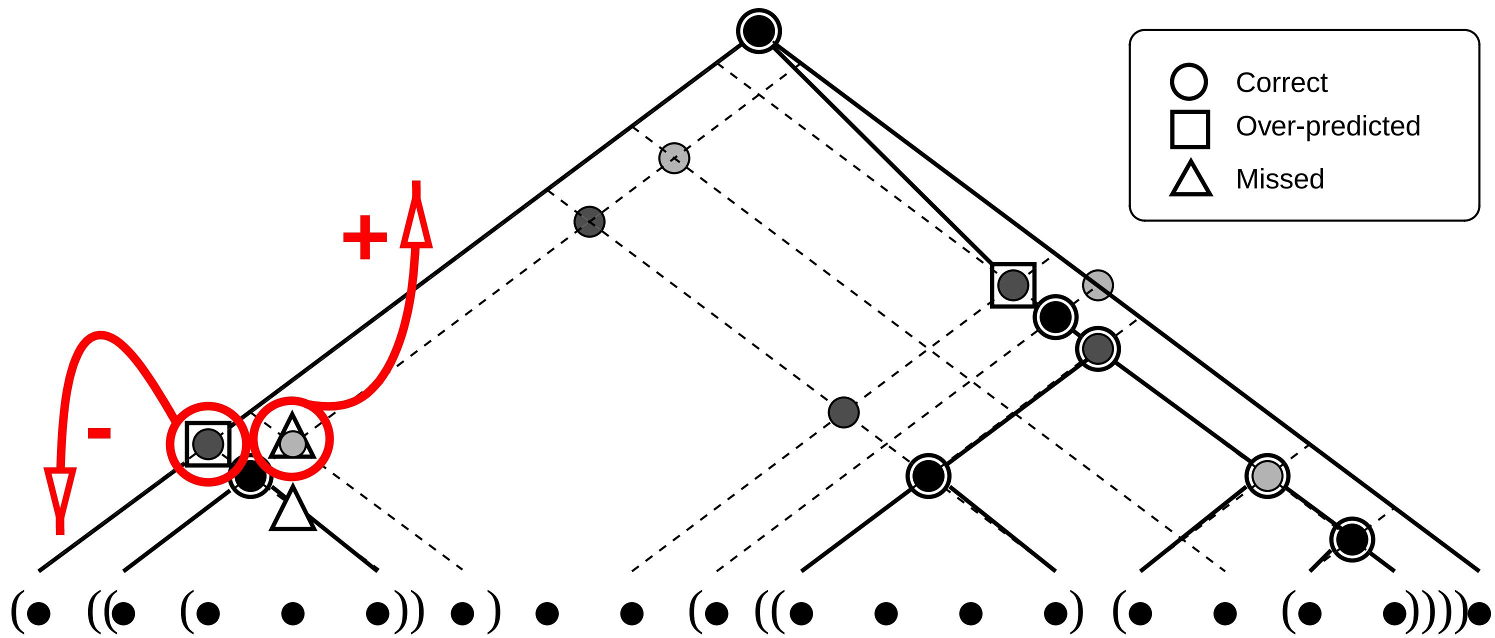

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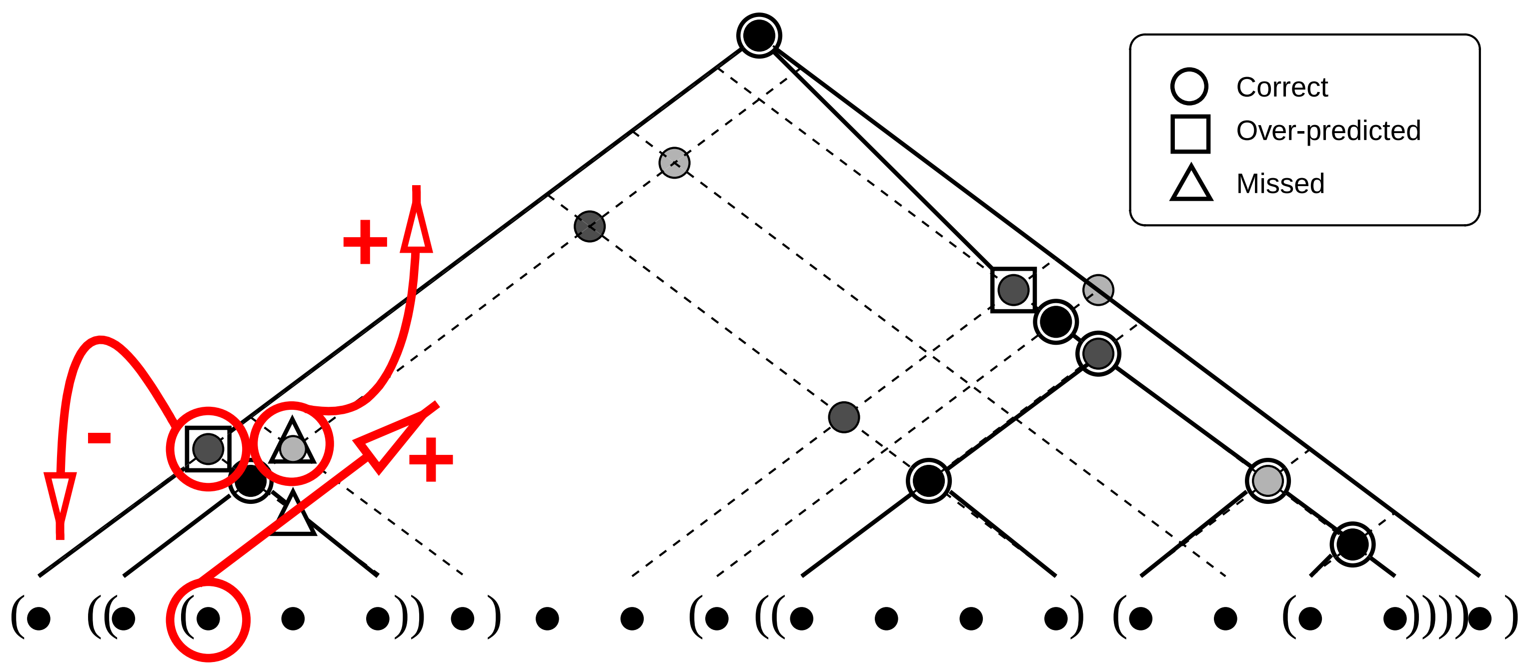

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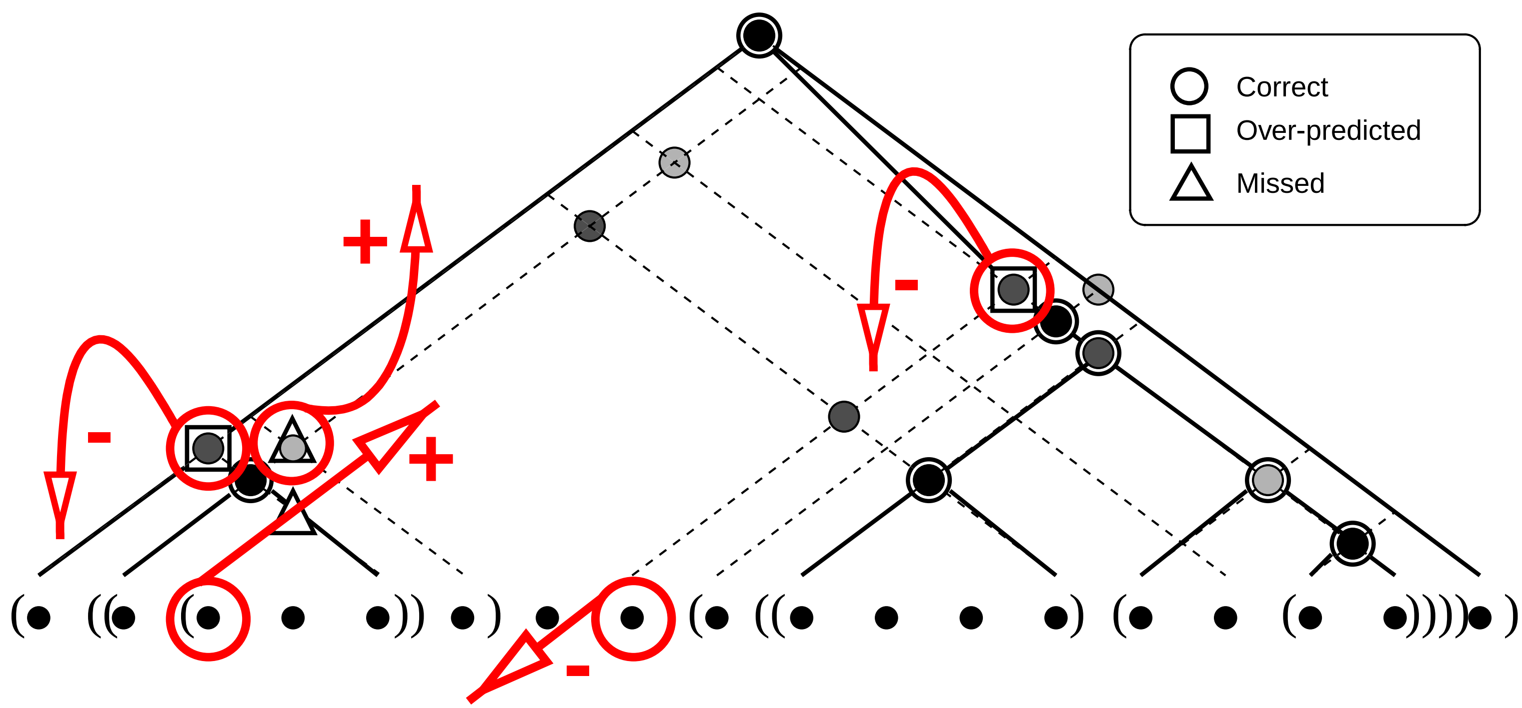

Learning Feedback: Example

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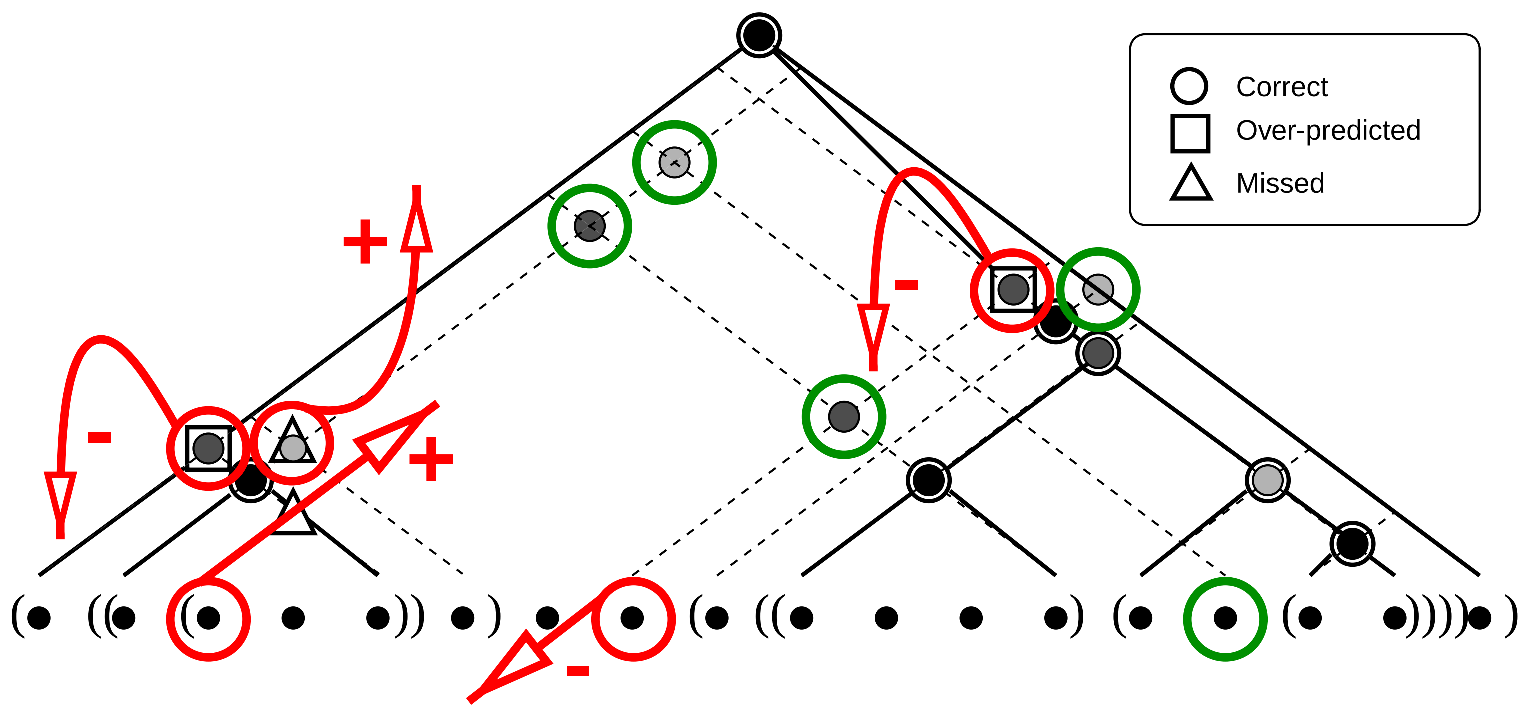


- Local predictions that do not hurt globally are **not penalized**

Empirical validation of FR-Perceptron

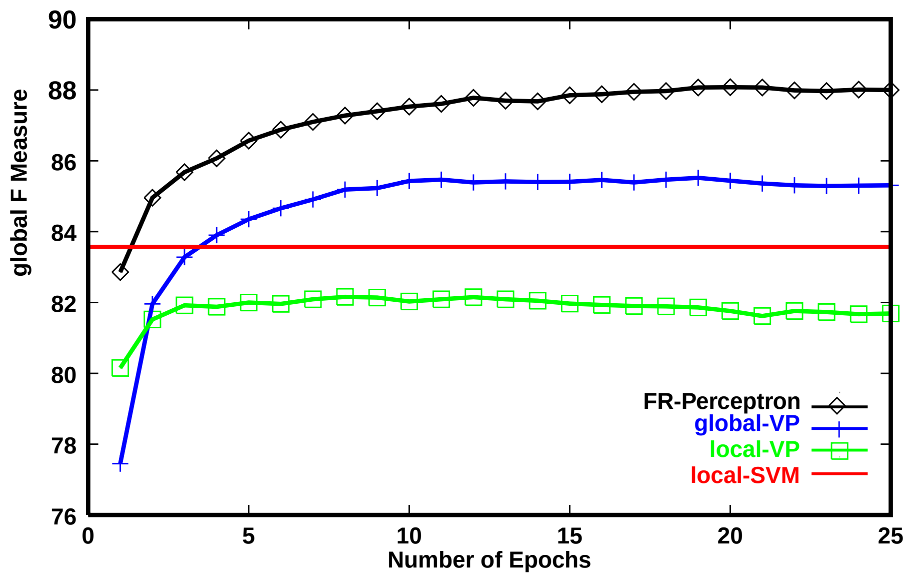
- We perform a number of experiments to validate the behavior of FR-Perceptron
- Problem: Clause Identification, following CoNLL-2001 Shared Task:
  - ⋆ One type of phrases: clauses
  - ⋆ Hierarchical Structure
  - ⋆ Training: $\sim$ 9,000 sentences, $\sim$ 25,000 clauses
  - ⋆ Test: $\sim$ 1,700 sentences, $\sim$ 4,900 clauses

Empirical validation of FR-Perceptron

We compare four training strategies for the Filtering-Ranking model:

	type	**w's trained**	**R on F**	**penalty wrt.**
local-VP	VP	separatedly	no	binary sign
local-SVM	SVM	separatedly	no	binary sign
global-VP	VP	together	yes	binary sign
FR-Perceptron	VP	together	yes	$\arg\max$

Empirical validation of FR-Perceptron
Overall Results



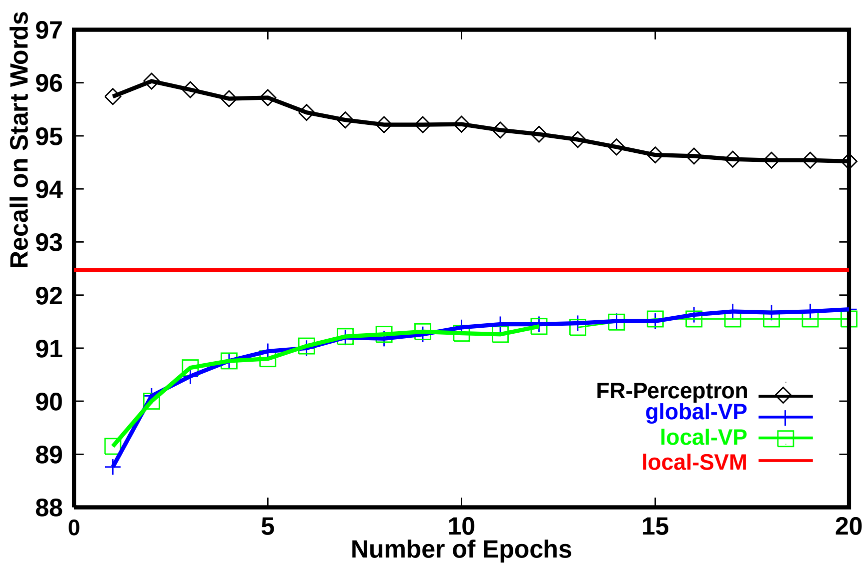
- Global training strategies perform better than local strategies
- Feedback after inference trains more effectively the recognizer

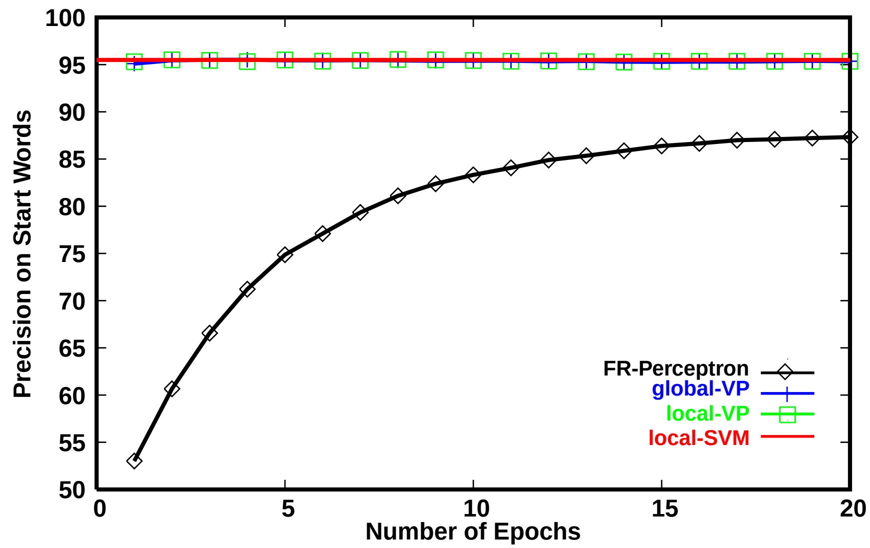
Empirical validation of FR-Perceptron
Behavior of the Start-End Filter

We look at the performance of Start-End functions:

- Precision/Recall of Start-End
- How much the phrase space is reduced?
- What is the maximum achievable F_1 after the Filter?

Empirical validation of FR-Perceptron Recall/Precision on Start words

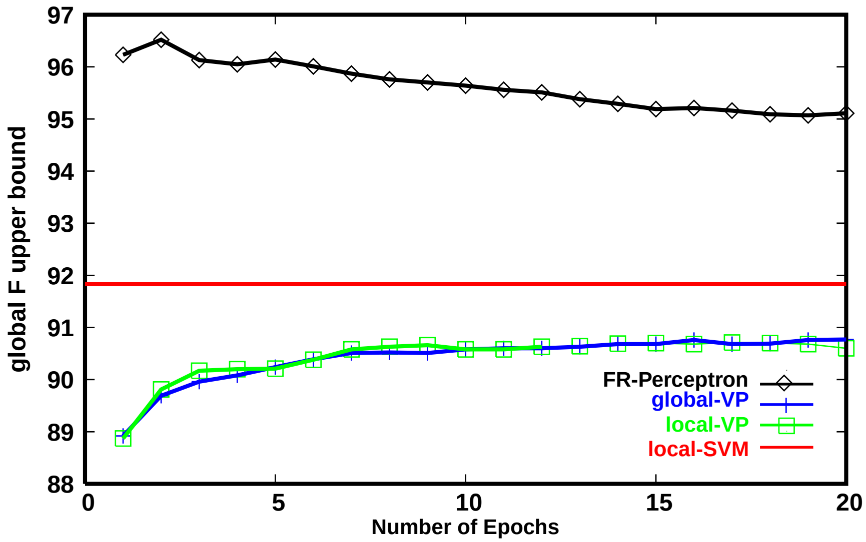


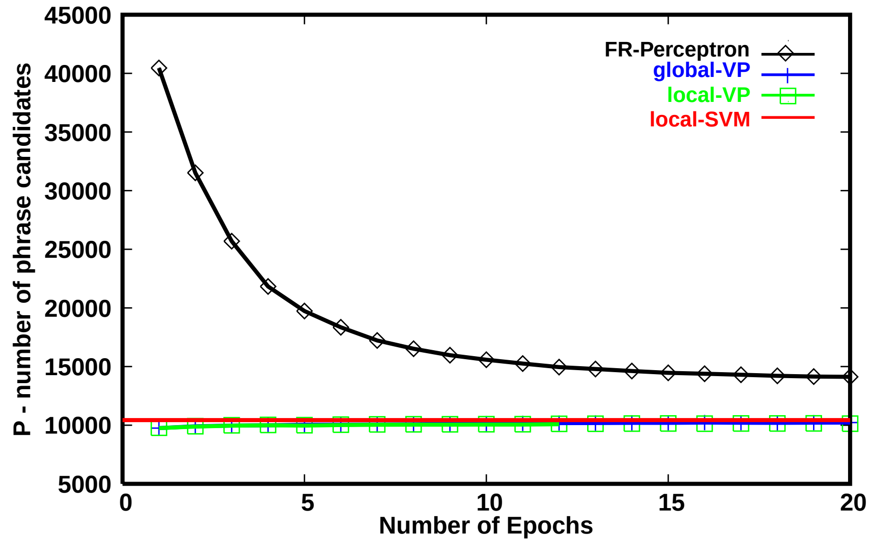


- FR-Perceptron favors recall, others favor precision

- On End words, the same behavior is observed

Experiments on Clause Identification
Upper Bound F_1/Explored Phrases



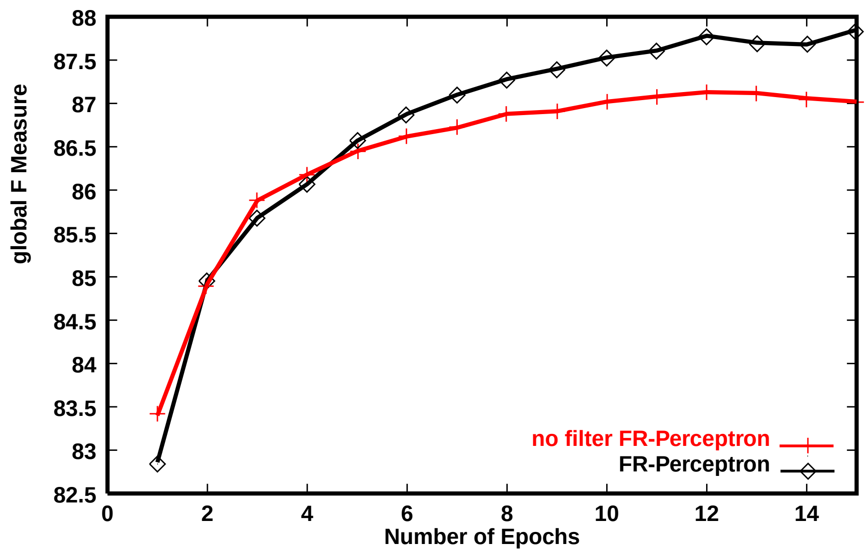


- FR-Perceptron maintains a high upper-bound F_1 for the ranking layer (left), and reduces the space of explored phrases (right)

- Other methods are not sensitive to F-R interactions

Empirical validation of FR-Perceptron
Does the Filter help in performance?

- We train the architecture without the Filter (UB-$F_1 = 100\%$):



- Filtering favors not only efficiency, but also global accuracy

Outline

- Introduction: Phrase Recognition
- Learning Methods for Text Analysis Tasks
- Filtering-Ranking Architecture
- Systems and Results on Syntactic-Semantic Parsing
- Conclusion and Future Research

Phrase Recognition in Syntactic-Semantic Analysis

- We apply the Filtering-Ranking architecture to three NLP recognition tasks
- We follow the CoNLL Shared Task settings

	edition	**nature**	$\lvert\mathcal{K}\rvert$	**structure**
NP Chunking	2000	syn.	1	sequential
Syntactic Chunking	2000	syn.	11	sequential
Clause Identification	2001	syn.	1	hierarchical
Semantic Role Labeling	2004	syn./sem.	20	seq./hier.

General Details about the Systems

- Averaged predictions: better convergence, better accuracy
- Feature Extraction functions:
  - ⋆ ϕ_{w} : window-based representations
  - ⋆ ϕ_{p} : patterns of the phrase candidate
  - ⋆ Both make use of predictions on the explored space:
    - ▷ Inference might lead to a sub-optimal, but accuracy is better
- Polynomial kernels of degree two:
  - ⋆ Much better than default linear predictions
  - ⋆ No improvement with higher degrees

Application to Syntactic Chunking

- Sequential structures:
  - ⋆ Chunks do not overlap
  - ⋆ Chunks do not admit embedding
- Inference: Viterbi-like dynamic programming
- Following the CoNLL-2000 Shared Task. Trained for:
  - ⋆ NP-Chunking: a single type of chunk, i.e. `NP`
  - ⋆ Syntactic Chunking: eleven types of chunks (`NP`,`VP`,`PP`,. . .)
- Many systems are evaluated on this benchmark data.
  All of them approach the problem as a tagging task.

Syntactic Chunking - Results

	Reference	Technique	Precision	Recall	F_1
	[Zhang 05]	SVD-ASO	94.57	94.20	94.39
	[Zhang 02]	Winnow	94.28	94.07	94.17
	[Kudo & Matsumoto 01]	SVM voting	93.89	93.92	93.91
	[Kudo & Matsumoto 01]	SVM single	93.95	93.75	93.85
▷	**FRP-Chunker**	**FR-Perceptron**	**94.20**	**93.38**	**93.79**
	[Zhang 05]	SVD	93.83	93.37	93.60
	[Zhang 02]	Winnow	93.54	93.60	93.57
	[Kudo & Matsumoto 00]	SVM	93.45	93.51	93.48
	[van Halteren 00]	MBL&WPD	93.13	93.51	93.32
	[Tjong Kim Sang 00]	MBL voting	94.04	91.00	92.50
	. . . + 8 shared task sytems more				

NP Chunking - Results

	Reference	scope	Technique	Prec.	Rec.	F_1
	[Zhang 05]	all	SVD-ASO	*unav.*	*unav.*	94.70
▷	FRP-Chunker	all	**FR-Perc.**	**94.55**	**94.37**	**94.46**
	[Kudo & Matsumoto 01]	all	SVM voting	94.47	94.32	94.39
	[Zhang 02]	all	Winnow	94.39	94.37	94.38
	[Sha & Pereira 03]	NP	CRF	*unav.*	*unav.*	94.38
▷	FRP-Chunker	NP	**FR-Perc.**	**94.69**	**93.98**	**94.33**
	[Kudo & Matsumoto 01]	all	SVM single	94.54	94.09	94.32
	[Sha & Pereira 03]	NP	MM-VP	*unav.*	*unav.*	94.09
	[Zhang 02]	all	Winnow	93.80	93.99	93.89
	[Collins 02]	NP	MM-VP	*unav.*	*unav.*	93.53
	...					

Application to Clause Identification

- A single type of phrases: clauses
- Clauses form hiearchical structures in a sentence
- Inference: CKY-like dynamic programming
- Following the CoNLL-2001 Shared Task

Clause Identification - Results

	Reference	Technique	Precision	Recall	F_1
▷	**FR-Clauser**	**FR-Perceptron**	**88.17**	**82.10**	**85.03**
	[Carreras et al. 02]	AdaBoost class.	90.18	78.11	83.71
	[Carreras & Màrquez 01]	AdaBoost class.	84.82	78.85	81.73
	[Molina & Pla 01]	HMM	70.85	70.51	70.68
	[Tjong Kim Sang 01]	Memory-based	76.91	65.22	70.58
	[Patrick & Goyal 01]	AdaBoost	73.75	64.56	68.85
	[Dejean 01]	Theory Ref.	72.56	58.69	64.89
	[Hammerton 01]	LSTM-NNet	55.81	49.49	52.46

Application to Semantic Role Labeling

- We follow the CoNLL-2004 Shared Task:
  puts SRL after partial parsing analysis (chunks and clauses)

- The SRL strategy looks for a hierarchy of arguments in a sentence, where:

  ⋆ Arguments are formed by joining elements found within clauses: words, chunks and inner clauses

  ⋆ An argument is related to number of verbs. These relations are labelled with semantic roles

- Other systems in literature approach the problem as a chunking task, recognizing arguments of different predicates independently

Semantic Role Labeling - Results

	Reference	Technique	Precision	Recall	F_1
	[Hacioglu et al. 04]	SVM	72.43	66.77	69.49
	[Punyakanok et al. 04]	Winnow	70.07	63.07	66.39
▷	FR-SRLabeler	**FR-Perceptron**	**71.81**	**61.11**	**66.03**
	[Lim et al. 04]	Max-Entropy	68.42	61.47	64.76
	[Park et al. 04]	SVM	65.63	62.43	63.99
	[Higgins 04]	TBL	64.17	57.52	60.66
	[van den Bosch et al. 04]	Memory-Based	67.12	54.46	60.13
	[Kouchnir 04]	Memory-Based	56.86	49.95	53.18
	[Baldewein et al. 04]	Max-Entropy	65.73	42.60	51.70
	[Williams et. al 04]	TBL	58.08	34.75	43.48

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Main Contributions (i): A Framework for Phrase Recognition

- We have studied the problem of recognizing phrase structures in a sentence.
  - ⋆ Many problems in NLP analysis can be casted as phrase recognition tasks

- We have discussed architectures based on learning and inference:
  - ⋆ Models based on decompositions at word and phrase level
  - ⋆ Incremental inference procedures
  - ⋆ Learning algorithms at local and global contexts

Main Contributions (ii): Filtering-Ranking Perceptron

- A novel architecture for general phrase recognition:
  - ⋆ Puts learning at phrase level
  - ⋆ Uses filtering to reduce the solution space
- FR-Perceptron:
  - ⋆ Global online learning, with ultra-conservative feedback
  - ⋆ Experiments show that FR-Perceptron trains the functions of the architecture as word filters and phrase rankers
  - ⋆ Analysis of convergence (see thesis)

Main Contributions (iii): Systems for Syntactic-Semantic analysis

- The Filtering-Ranking architecture is general and flexible
- We have developed Filtering-Ranking systems for three CoNLL Shared Tasks
- In all cases, we obtain results among the top in the state-of-the-art
- On Clause Identification, our system obtains the best results

Future Lines (i)

- From Greedy to Exact Inference in Global Learned Models
  - ⋆ We would like to test the influence of different inference strategies, in models that exploit increasing levels of dependencies
- Learning Issues for FR-Perceptron
  - ⋆ Gain theoretical understanding on the filtering-ranking interactions
- On Natural Language Tasks
  - ⋆ Joint analysis of several layers: e.g., PoS tagging + Chunking
  - ⋆ Increasing levels of syntax, from shallow, to partial, to full

Future Lines (ii)

- Introducing Knowledge
  - ⋆ Learn on the top of a grammar-based exploration
- On Representations and Kernels
  - ⋆ Look for more efficient kernel-based representations

Selected Publications (i): Learning Architectures

- Xavier Carreras, Lluís Màrquez and Jorge Castro
  "Filtering-Ranking Perceptron Learning for Partial Parsing"
  Machine Learning. 2005.

- Xavier Carreras and Lluís Màrquez
  "Online Learning via Global Feedback for Phrase Recognition"
  In *Proceedings of NIPS-2003*. Vancouver, Canada. 2003.

- Xavier Carreras, Lluís Màrquez, Vasin Punyakanok and Dan Roth
  "Learning and Inference for Clause Identification"
  In *Proceedings of ECML-2002*. Helsinki, Finland. 2002.

Selected Publications (ii): Shared Task Systems

- Xavier Carreras, Lluís Màrquez and Grzegorz Chrupała
  "Hierarchical Recognition of Propositional Arguments with Perceptrons", CoNLL-2004
- Xavier Carreras, Lluís Màrquez and Lluís Padró
  "A Simple Named Entity Extractor Using AdaBoost", CoNLL-2003
- Xavier Carreras, Lluís Màrquez and Lluís Padró
  "Learning a Perceptron-Based Named Entity Chunker via Online Recognition Feedback", CoNLL-2003
- Xavier Carreras, Lluís Màrquez and Lluís Padró
  "Named Entity Extraction using Adaboost", CoNLL-2002
- Xavier Carreras and Lluís Màrquez
  "Boosting Trees for Clause Splitting", CoNLL-2001

Selected Publications (iii): Shared Task Organization

- Xavier Carreras and Lluís Màrquez
  "Introduction to the CoNLL-2005 Shared Task: Semantic Role Labeling"
  In *Proceedings of CoNLL-2005*, Ann-Arbor, USA. 2005.

- Xavier Carreras and Lluís Màrquez
  "Introduction to the CoNLL-2004 Shared Task: Semantic Role Labeling"
  In *Proceedings of CoNLL-2004*, Boston, USA. 2004.

Gràcies!