Learning to Prune: Exploring the Frontier of Fast & Accurate Inference

Tim Vieira & Jason Eisner
Johns Hopkins University

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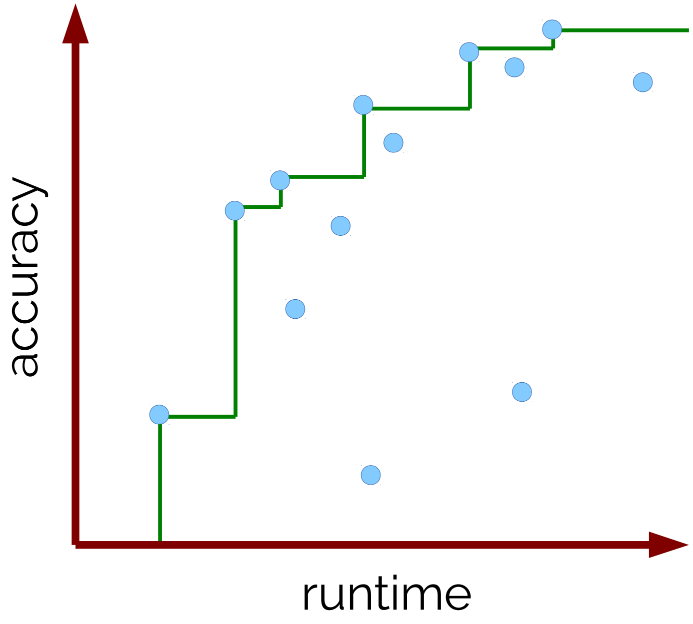
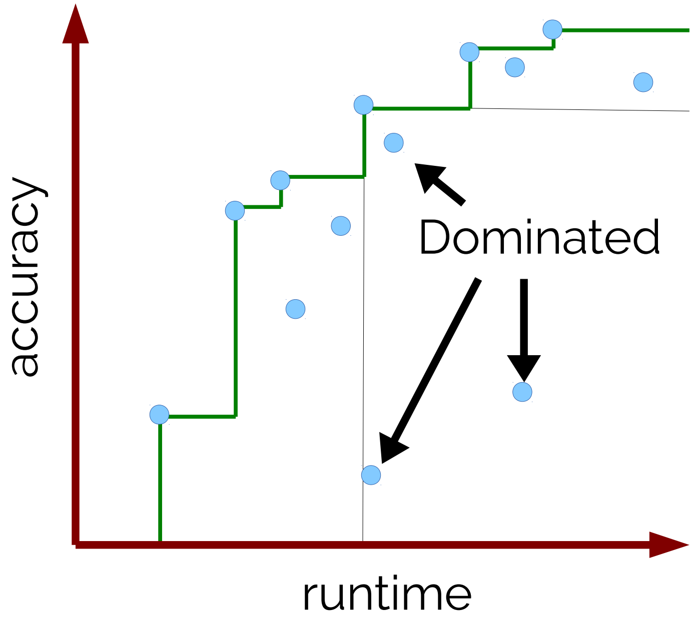
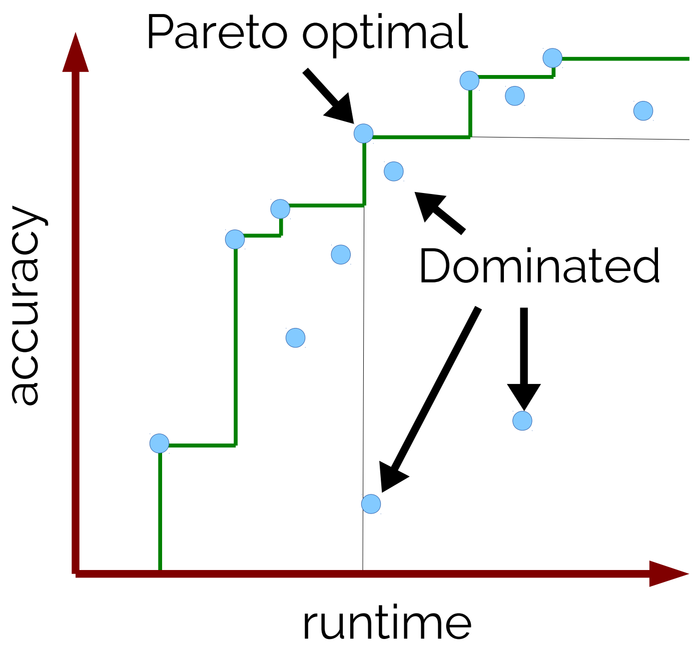
Exploring the Pareto Frontier of Fast & Accurate Inference



Exploring the Pareto Frontier of Fast & Accurate Inference



Pareto
Exploring the ^ Frontier of Fast & Accurate Inference



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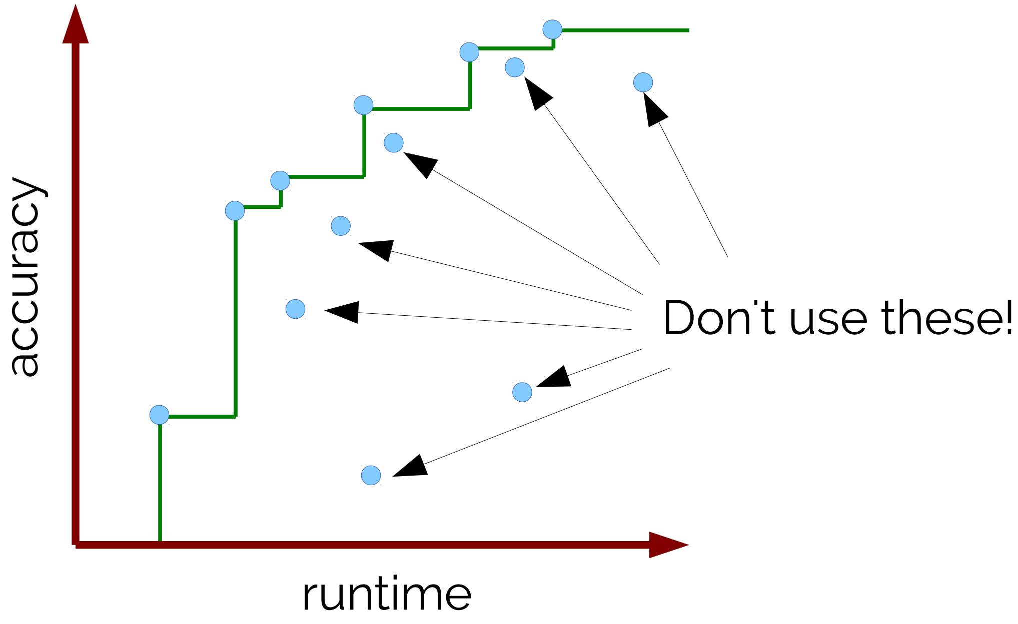

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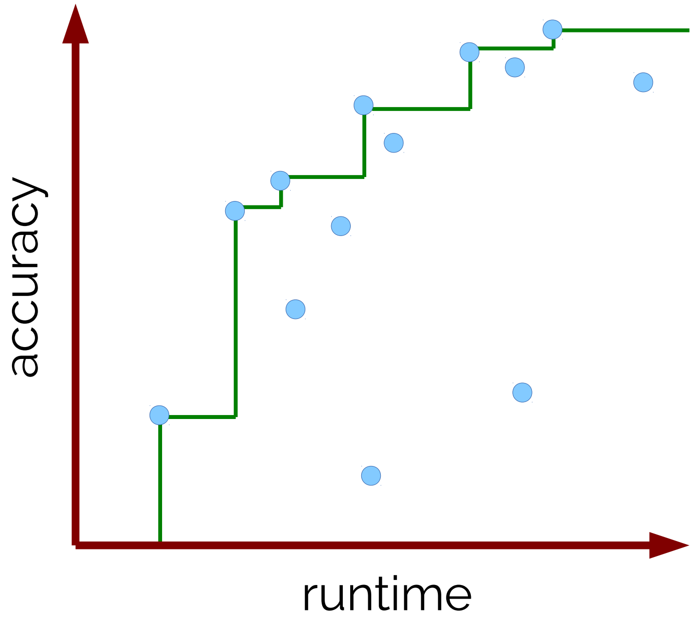
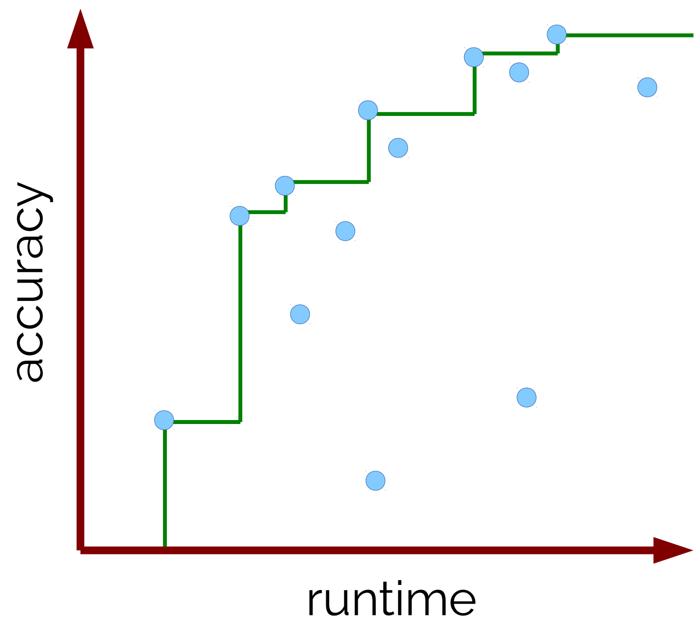


Search a space of approximate inference policies using machine learning

Pareto

Exploring the Frontier of Fast & Accurate Inference



Search a space of approximate inference policies using machine learning

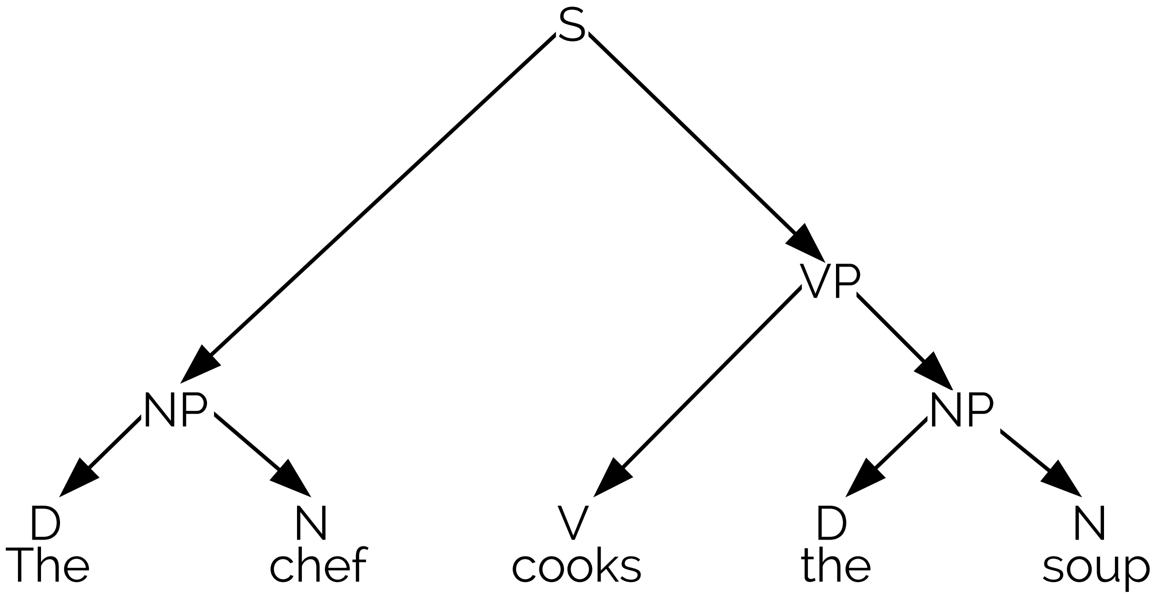
Want better algorithms? Use data, not just theory!

Outline

- Background
- Learning to prune
- Learning algorithm
- Making learning fast
  - Change propagation
  - Dynamic programming
- Results & conclusions

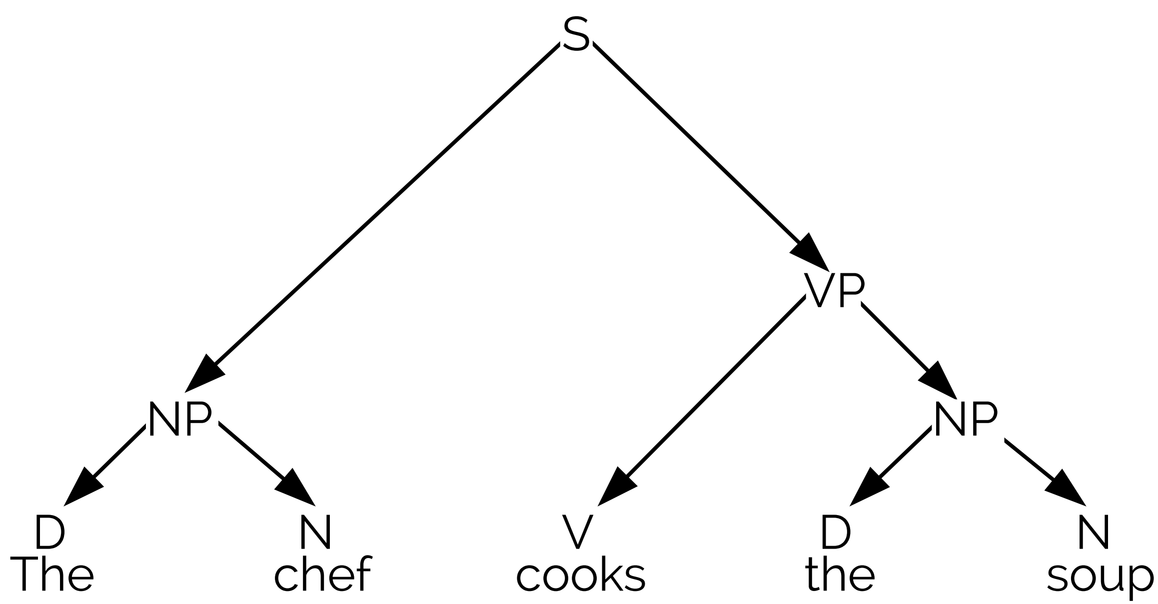
Parsing

"Diagramming sentences"



Parsing

What is a good derivation for this sentence?



p(d) =

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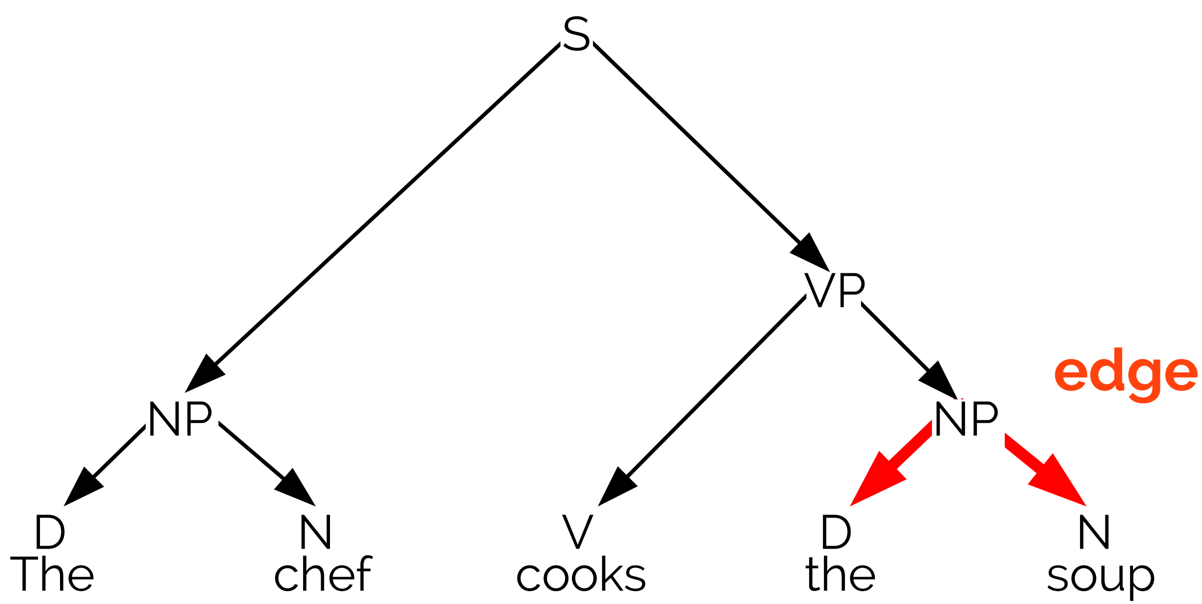

p(d) = g(NP → D N)

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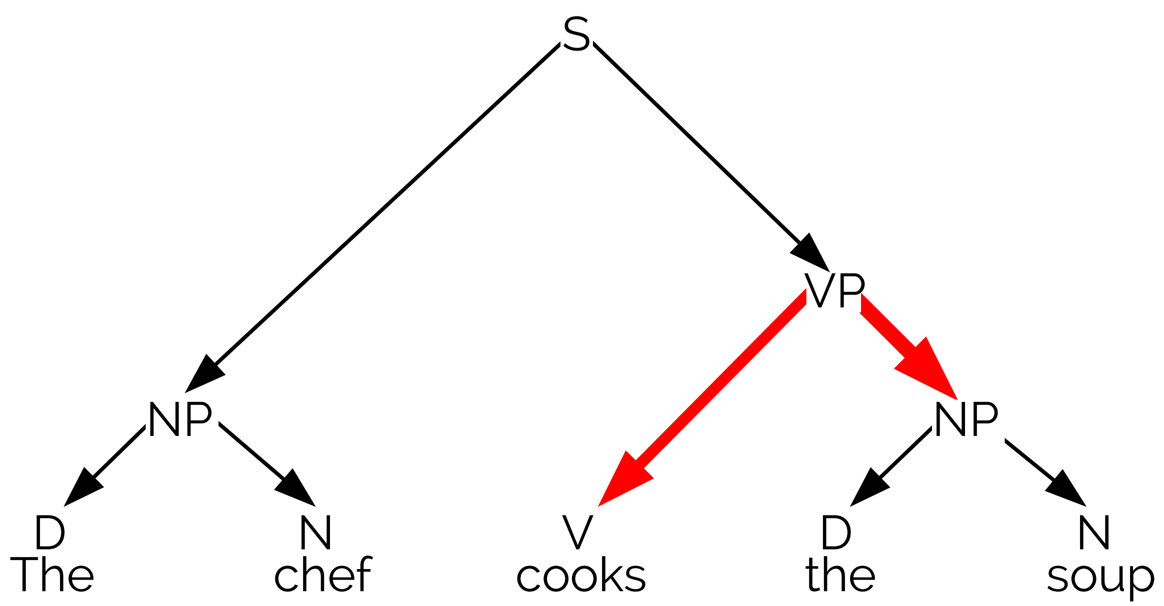

p(d) = g(NP → D N) * g(VP → V NP)

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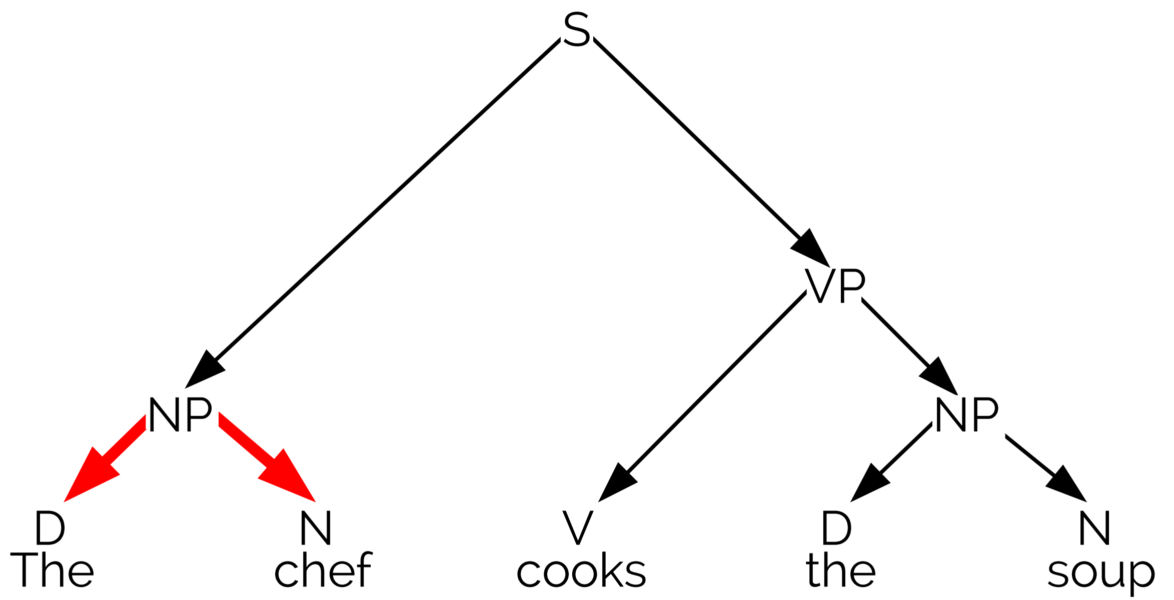

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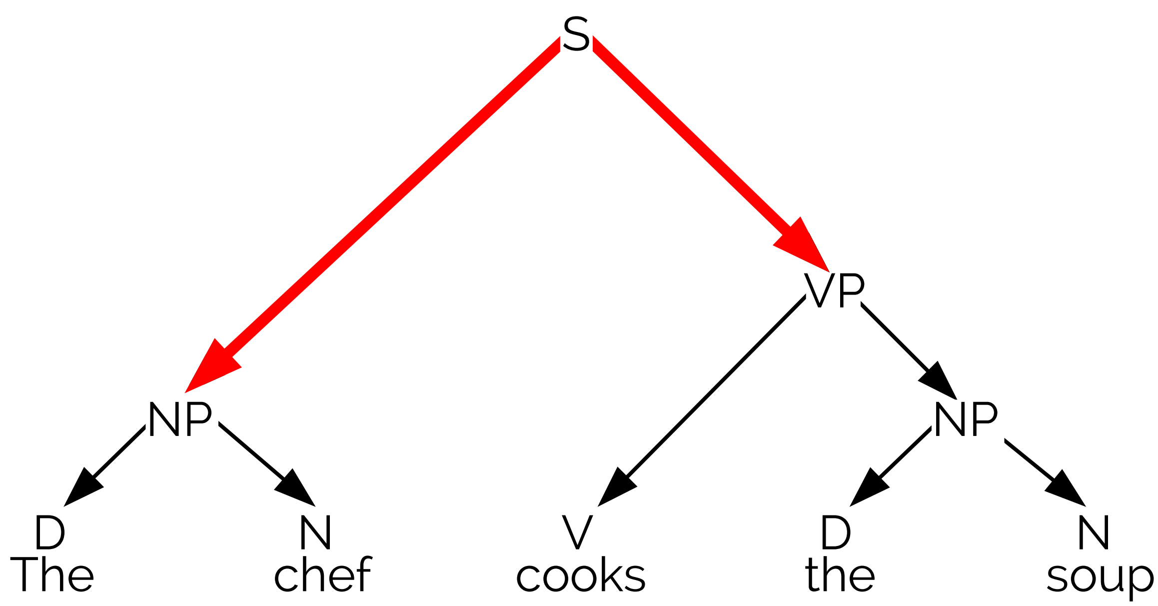
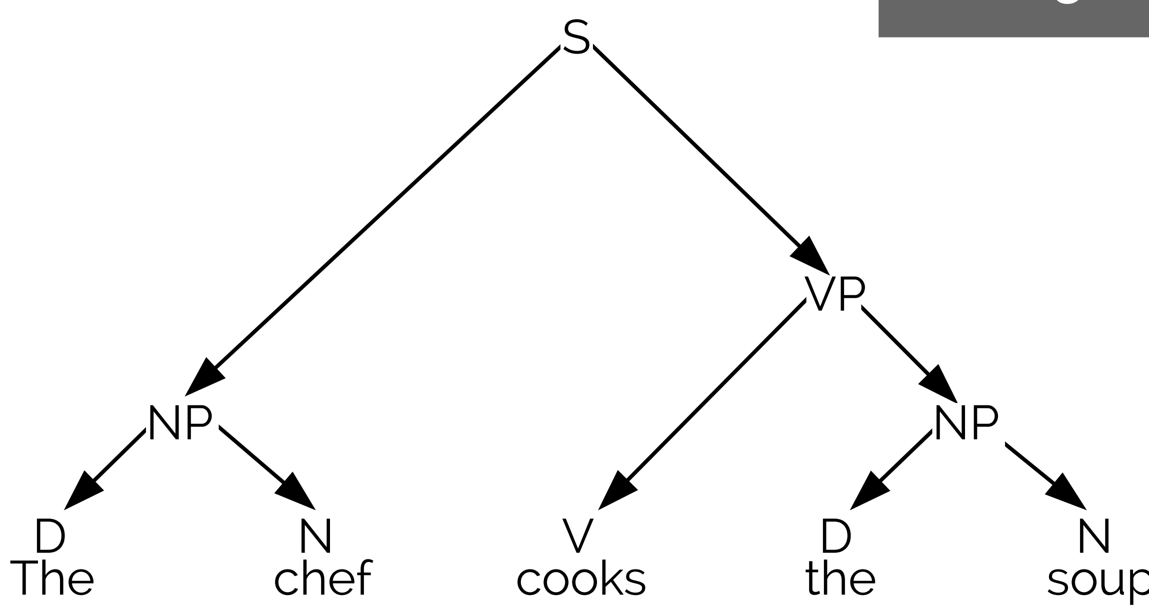


p(d) = g(NP → D N) * g(VP → V NP) * g(NP → D N) * g(S → NP VP)

Parsing

What is a good derivation for this sentence?

Scoring function is learned.



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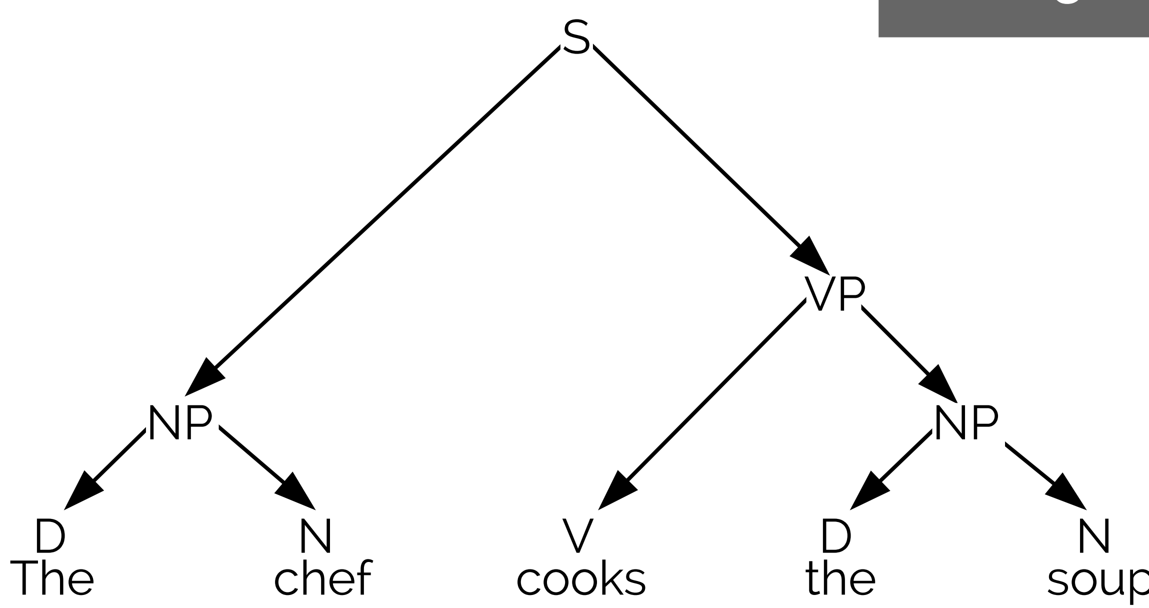
Grammar

S → NP VP
VP → V NP
NP → D N
D → the
V → cooks
N → chef
N → soup



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For this talk, I'll assume it's given.

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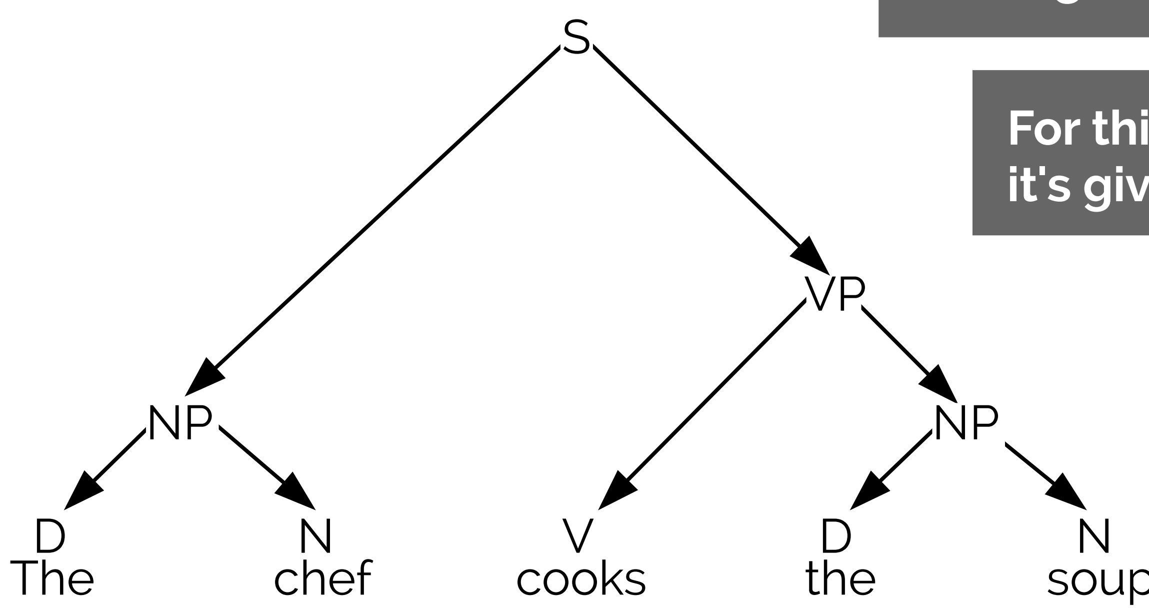

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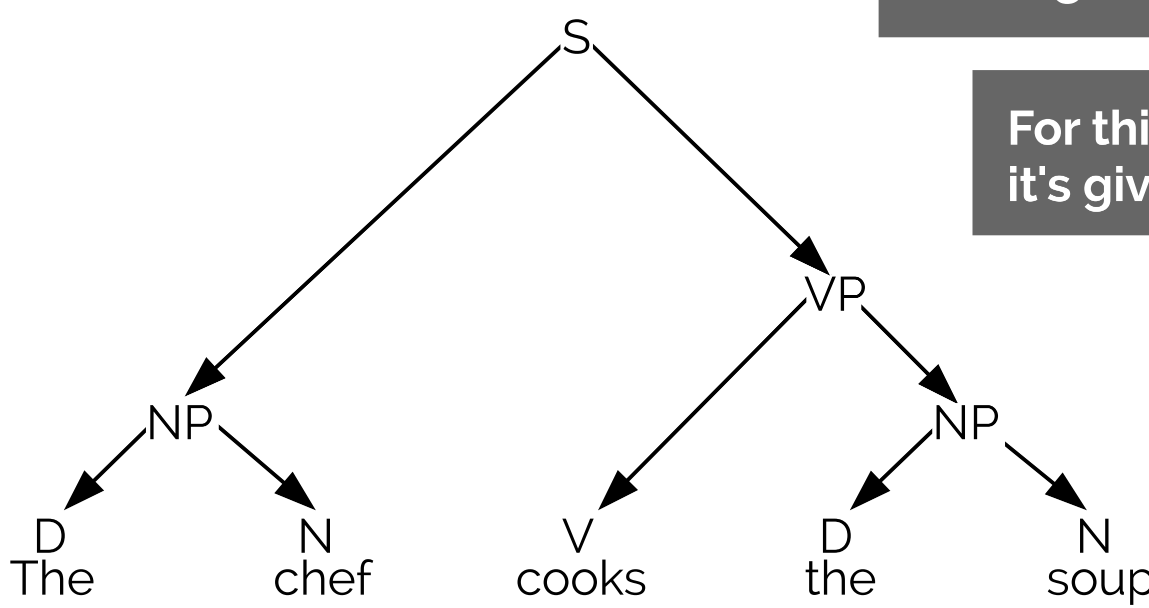

Written more generally, product of edge weights

$$p(d) = \prod_{e \in d} k_e$$

Parsing

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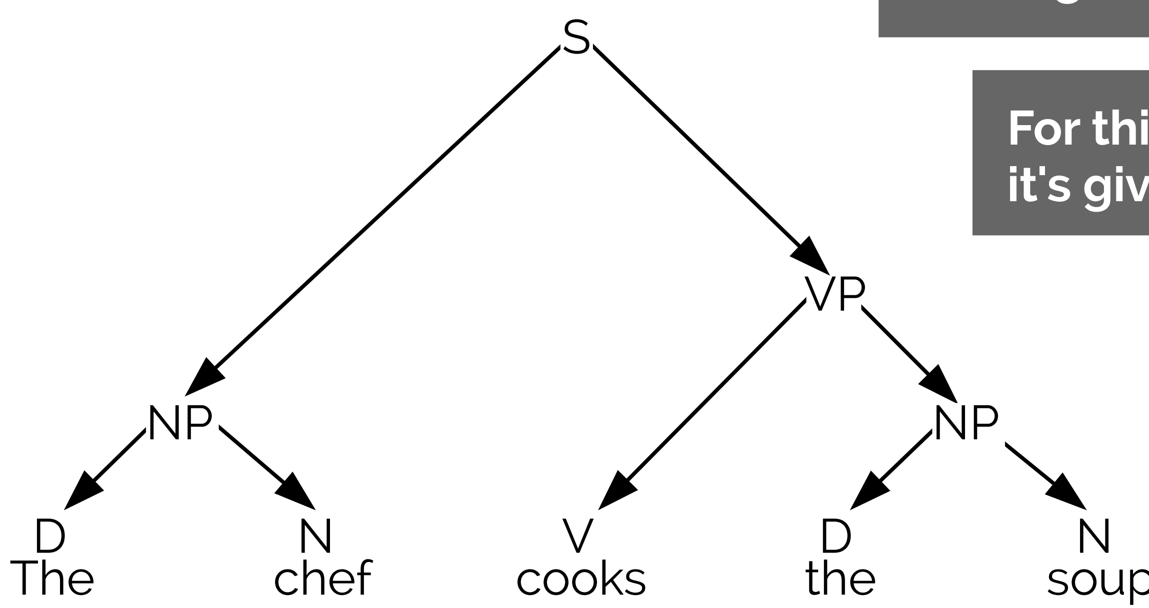
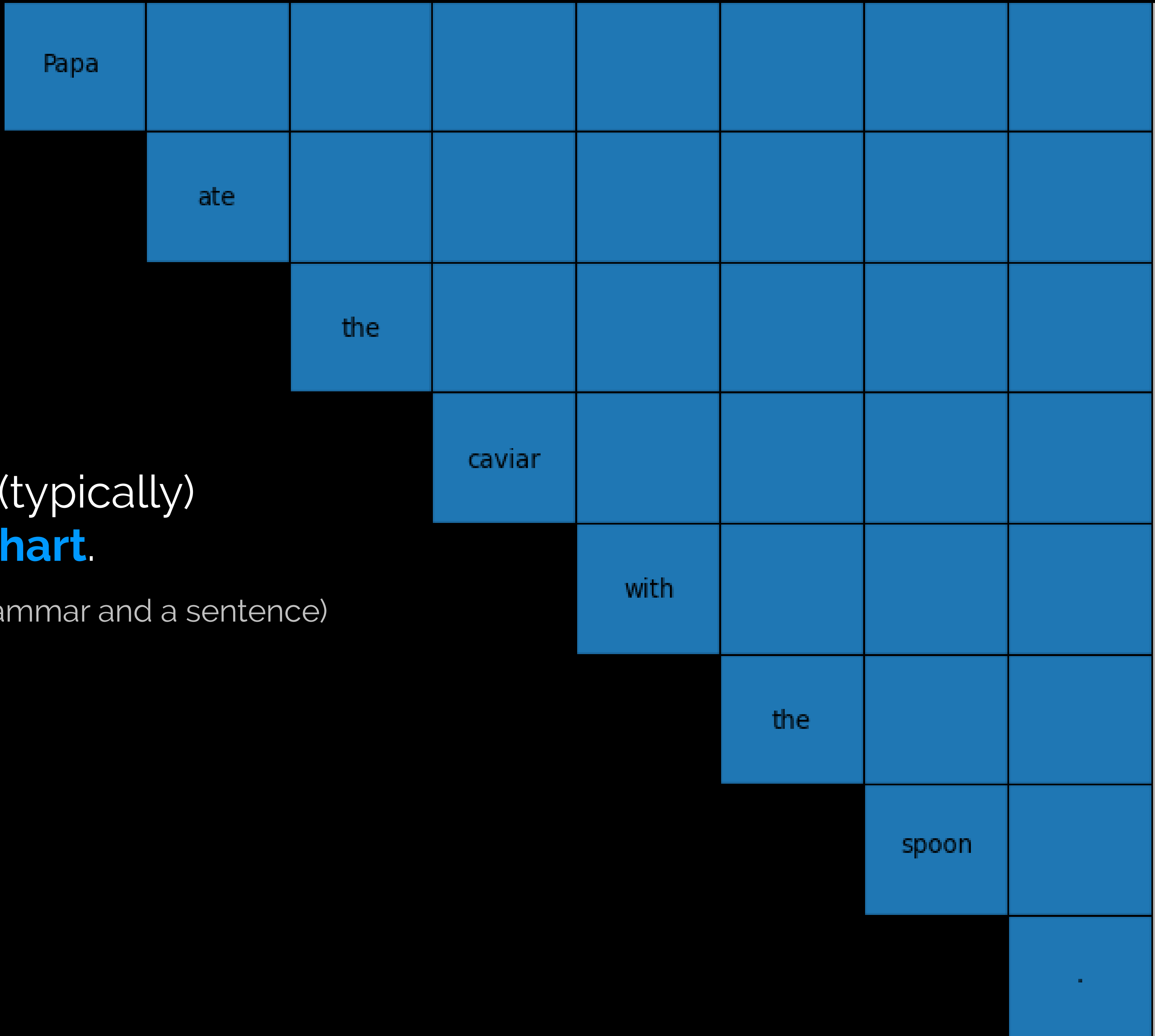


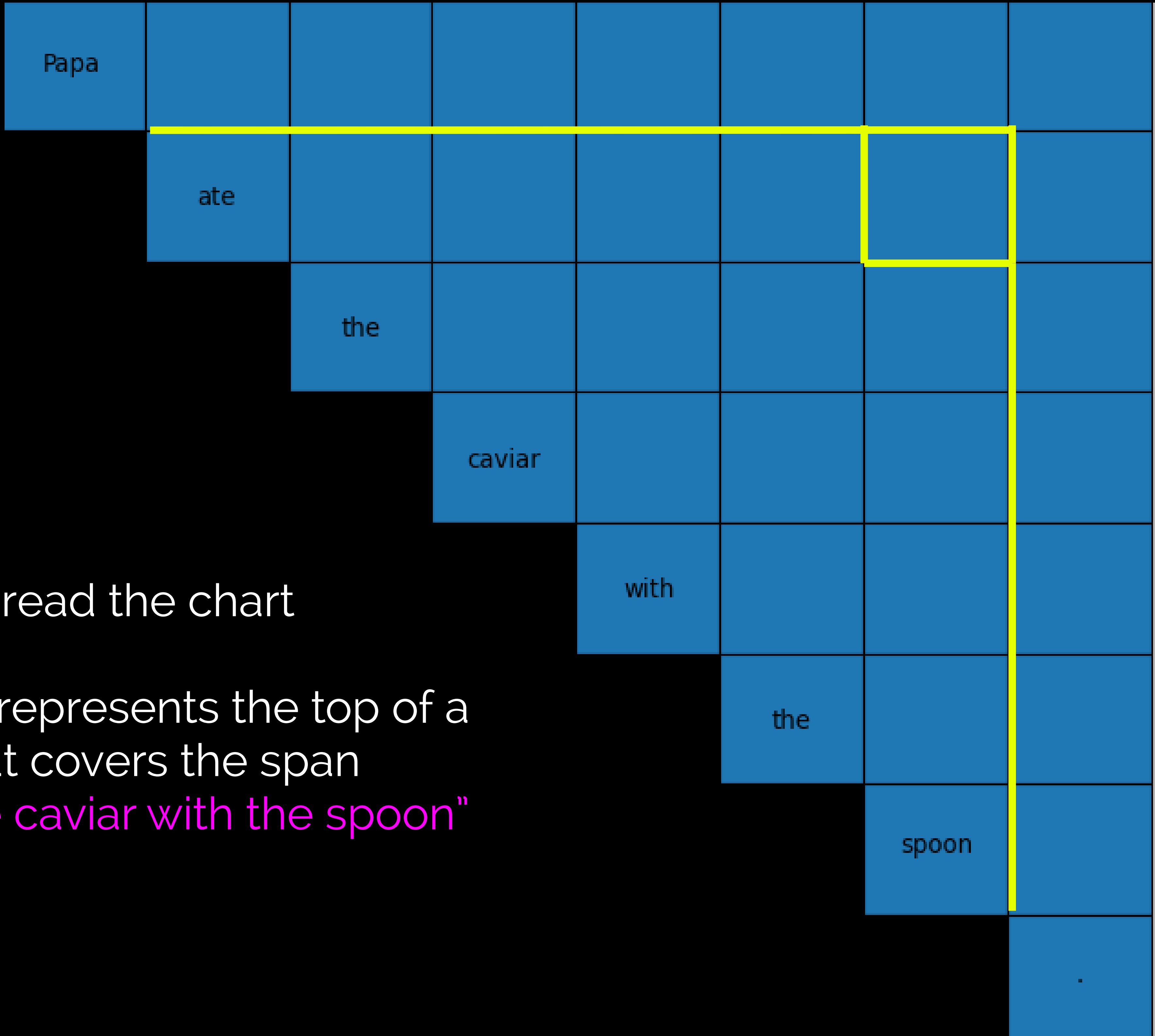
$$\underset{d \in D}{\operatorname{argmax}}\, p(d) = \underset{d \in D}{\operatorname{argmax}} \prod_{e \in d} k_e$$

How does a parser work?

Parsers (typically) fill in a **chart**.

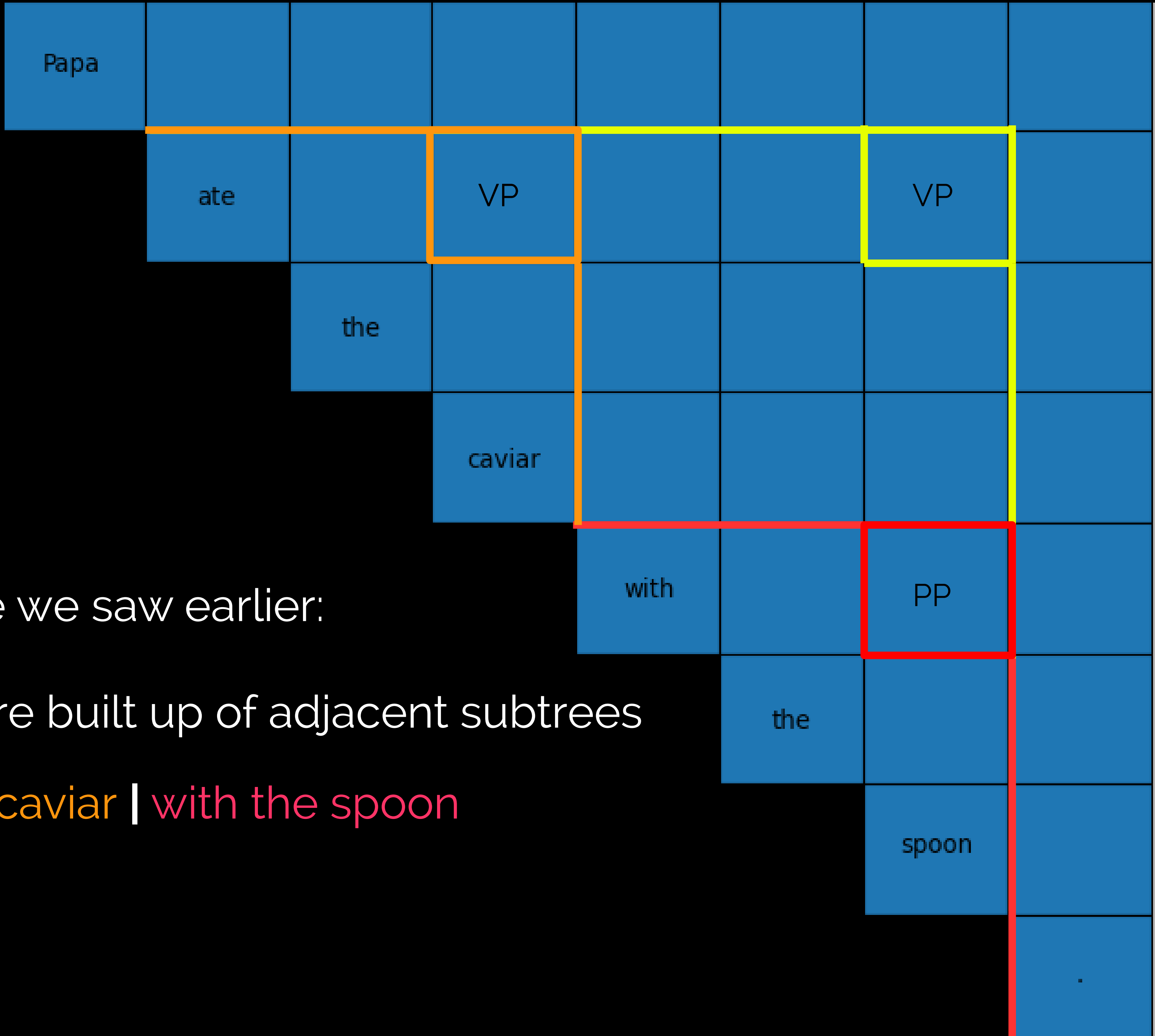
(Given a grammar and a sentence)





How to read the chart

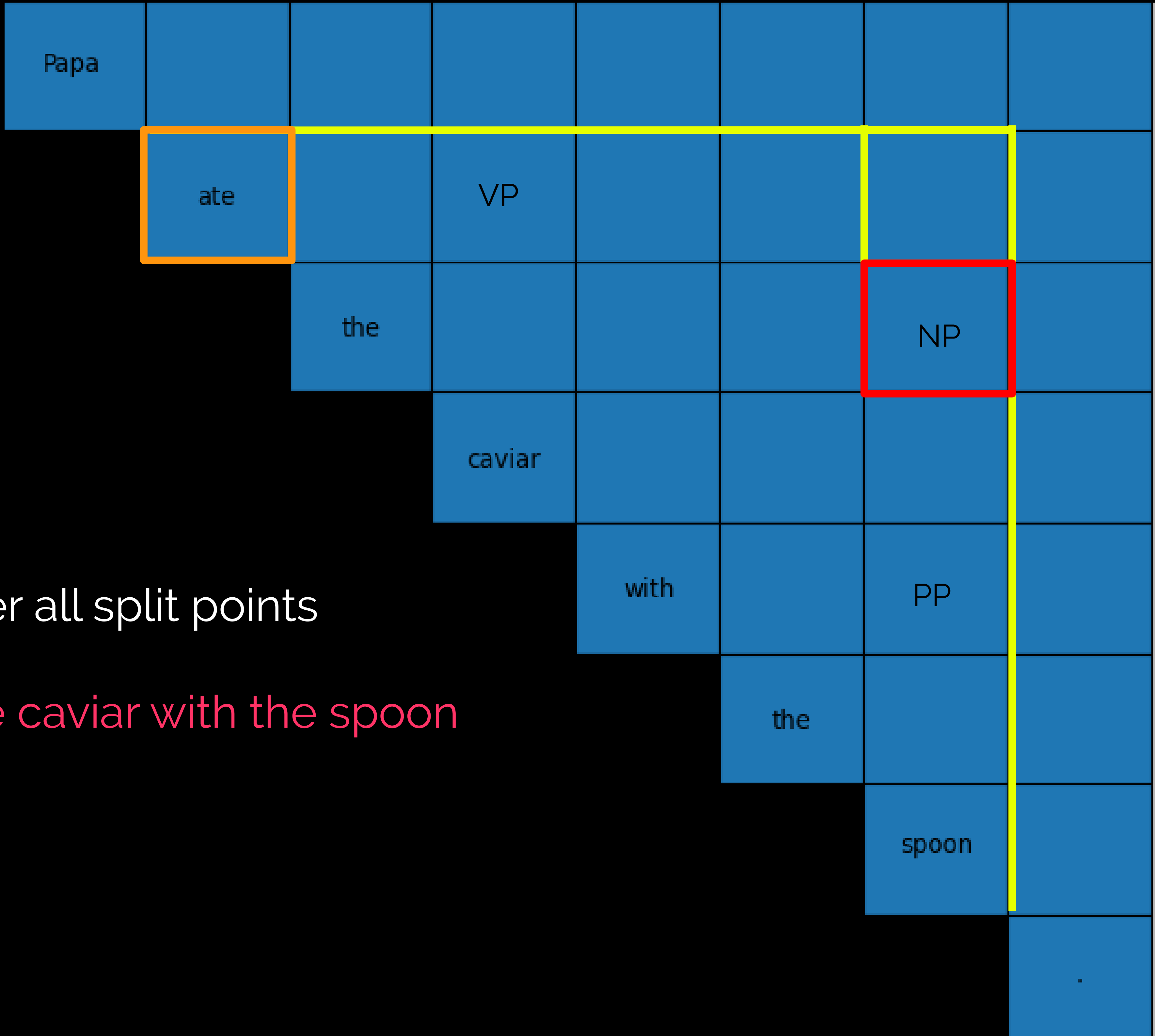
Yellow represents the top of a tree that covers the span "ate the caviar with the spoon"



Just like we saw earlier:

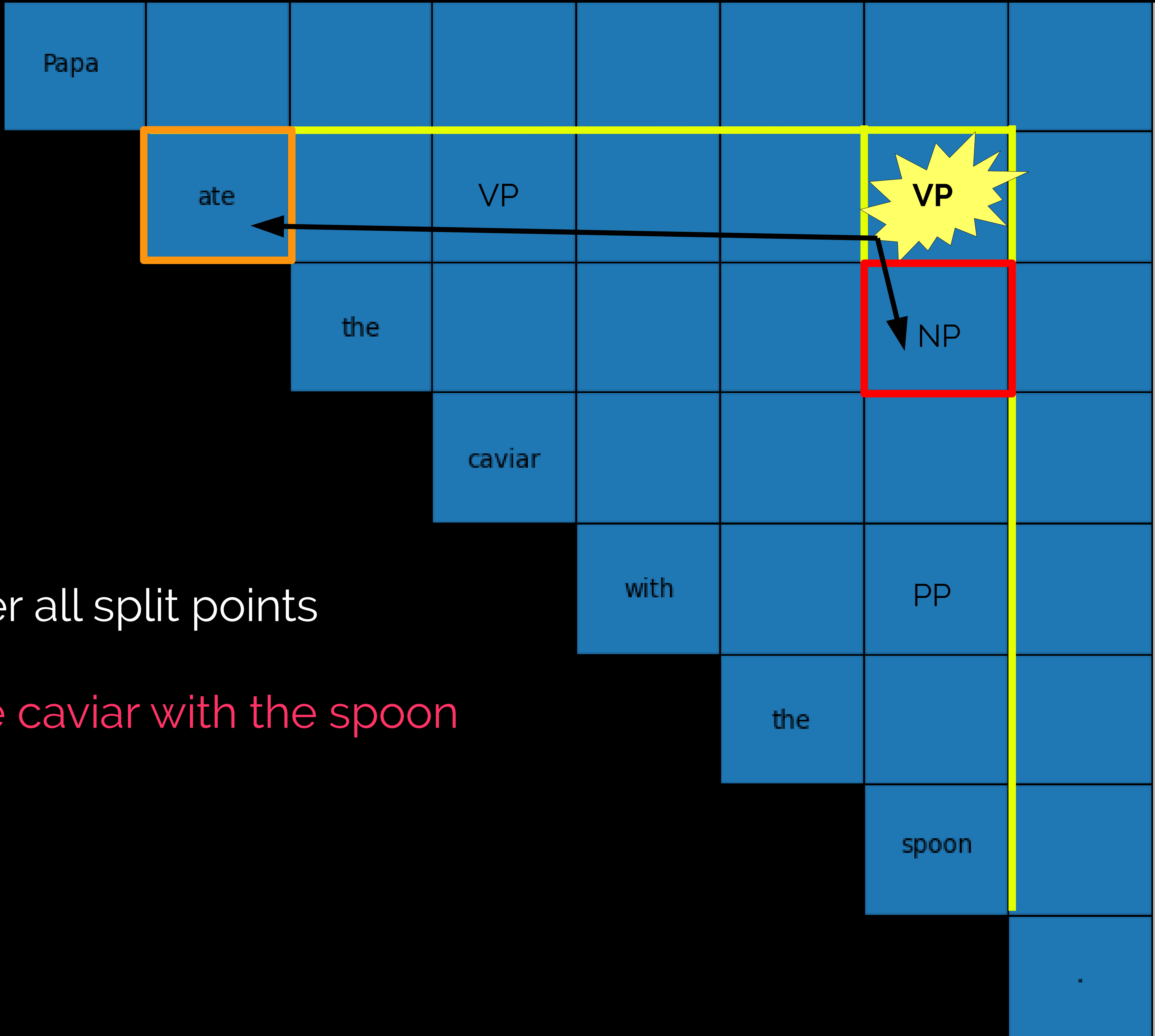
Trees are built up of adjacent subtrees

ate the caviar | with the spoon



Consider all split points

ate | the caviar with the spoon



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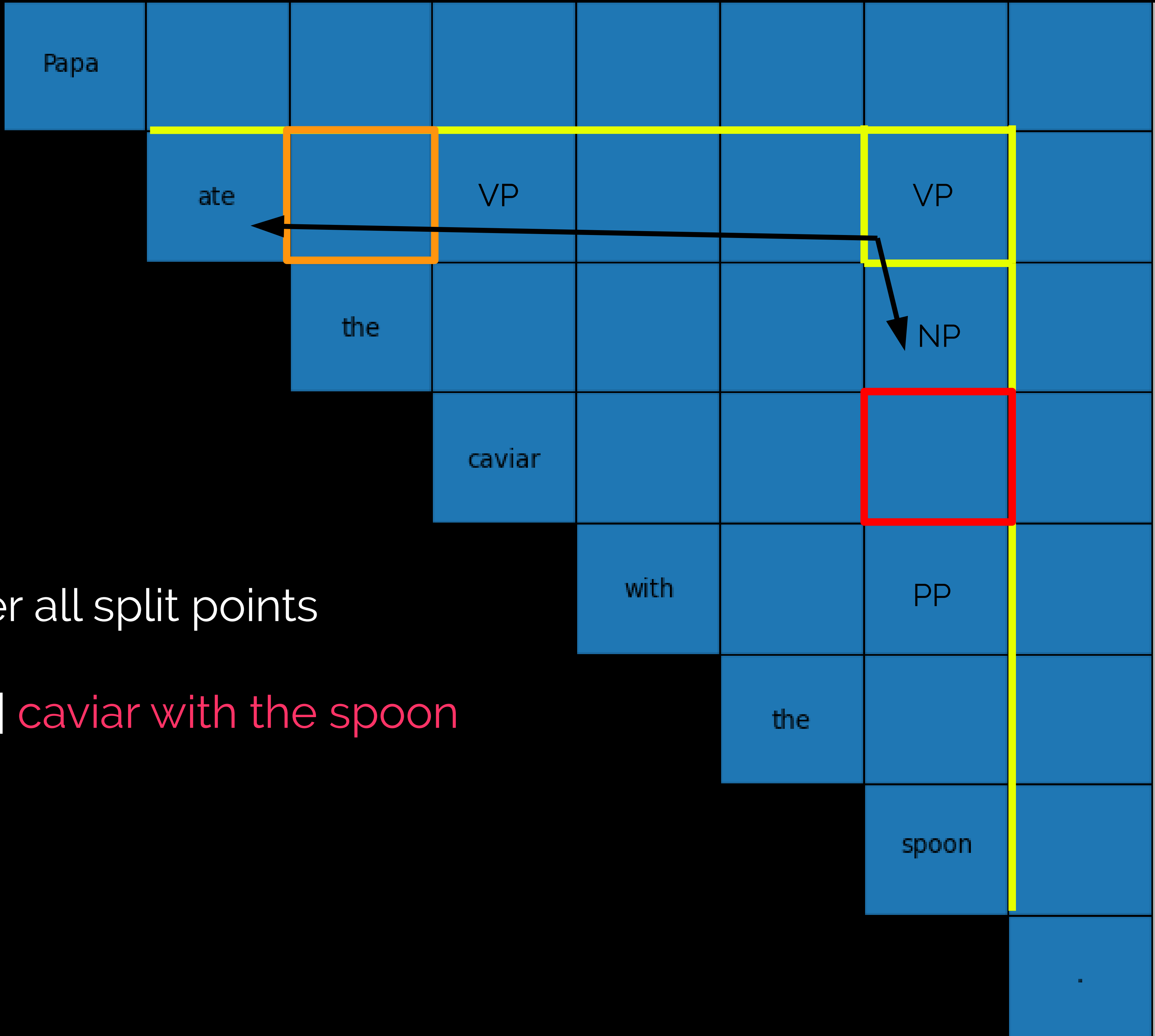

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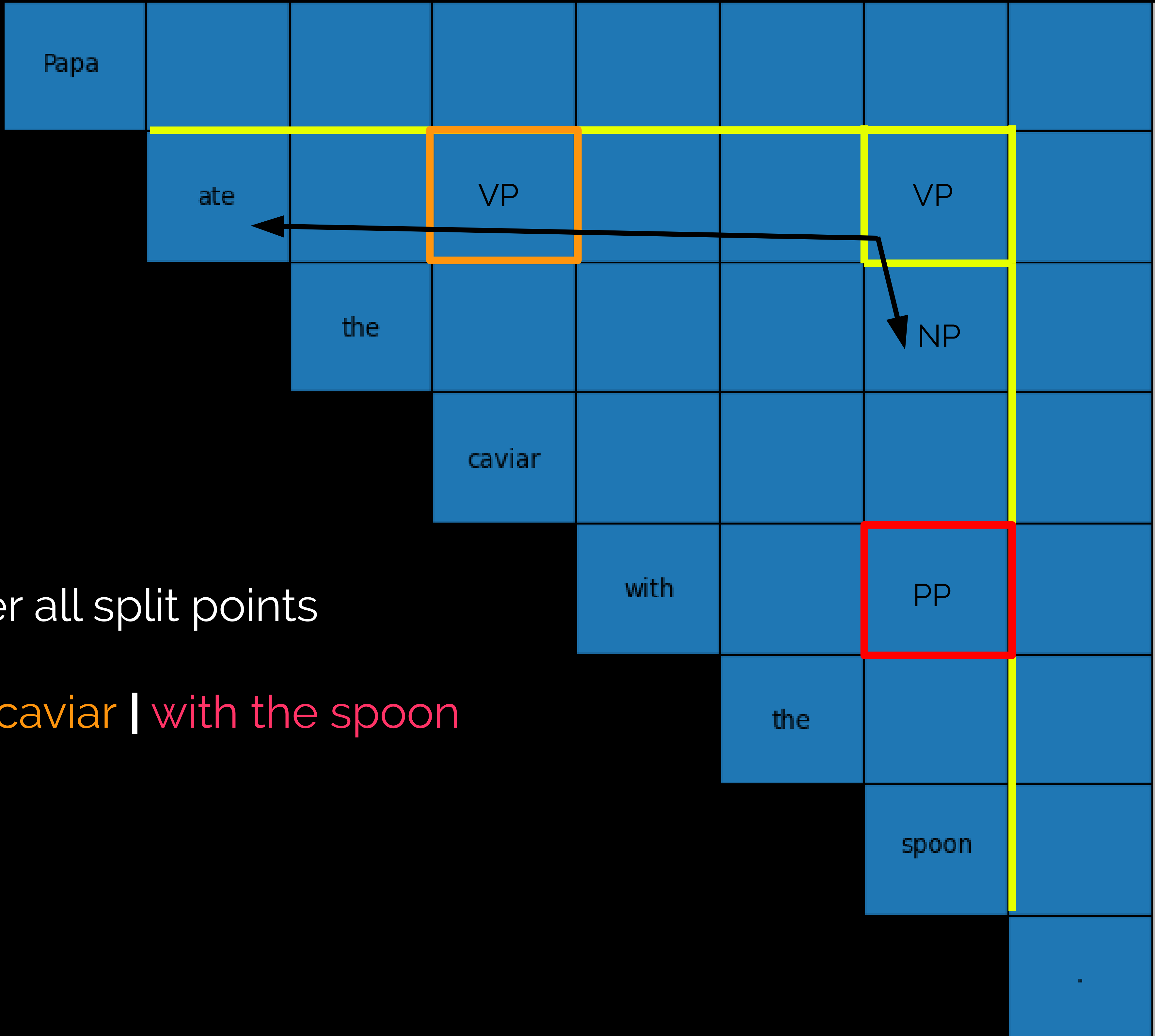

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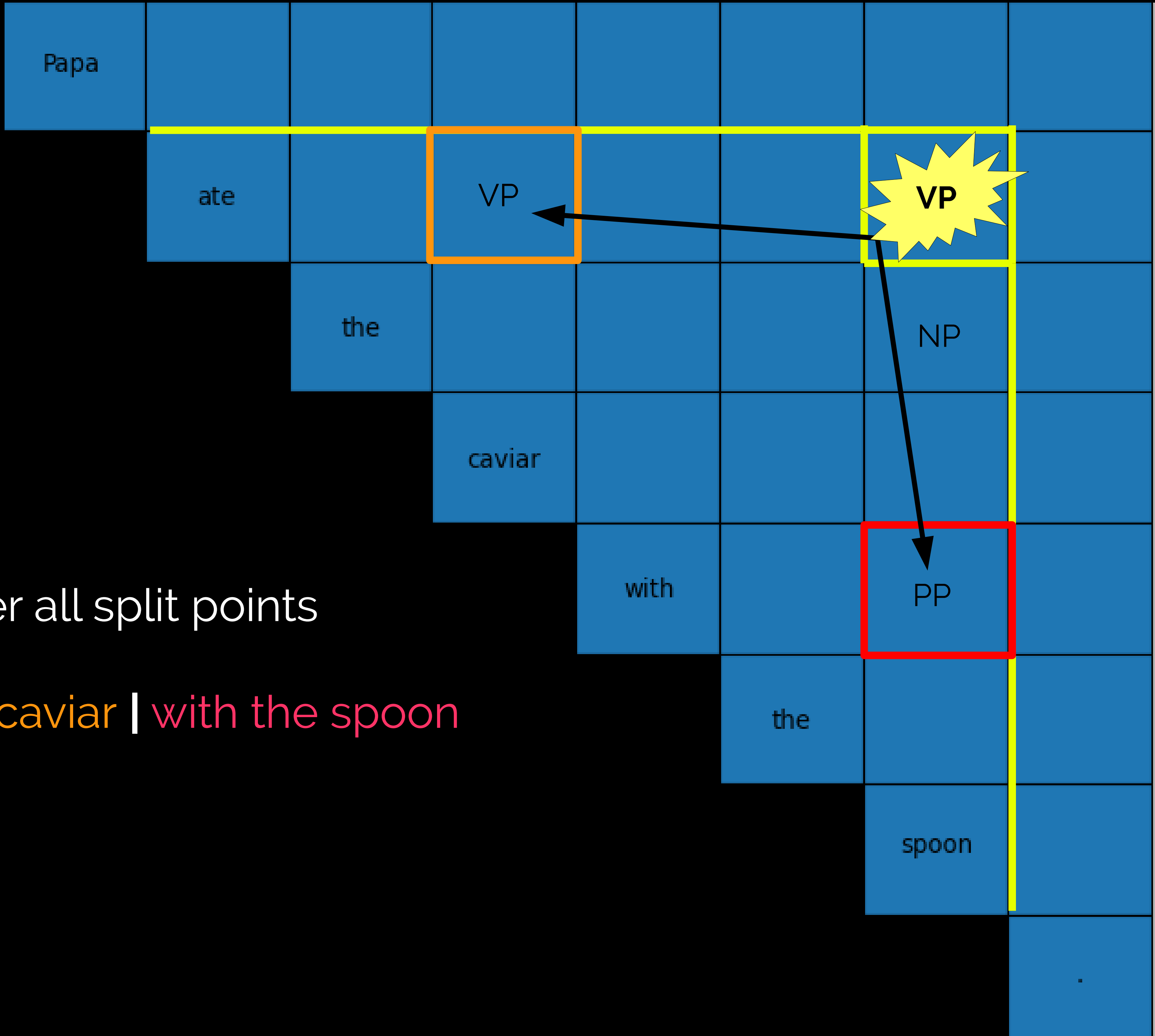

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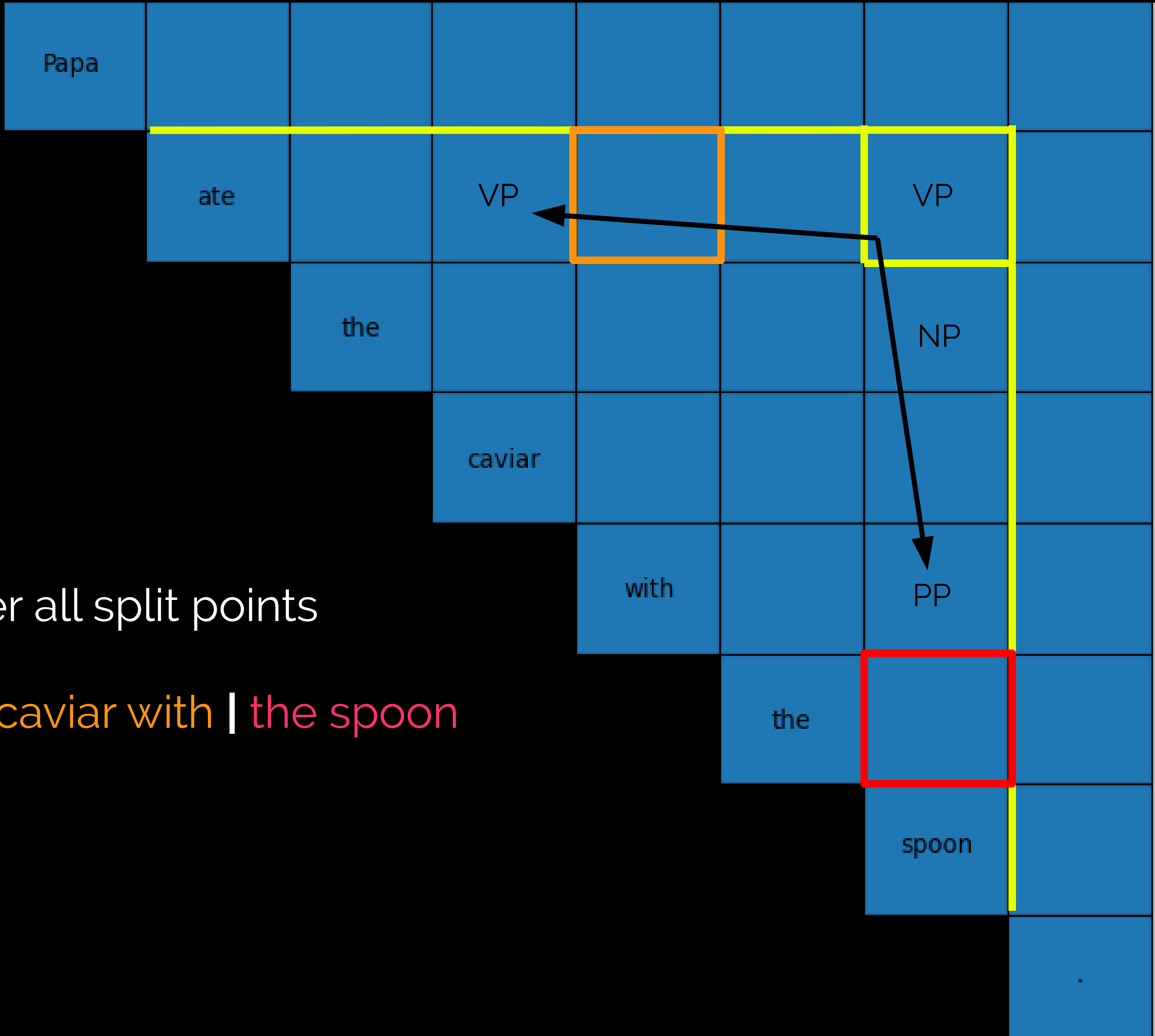

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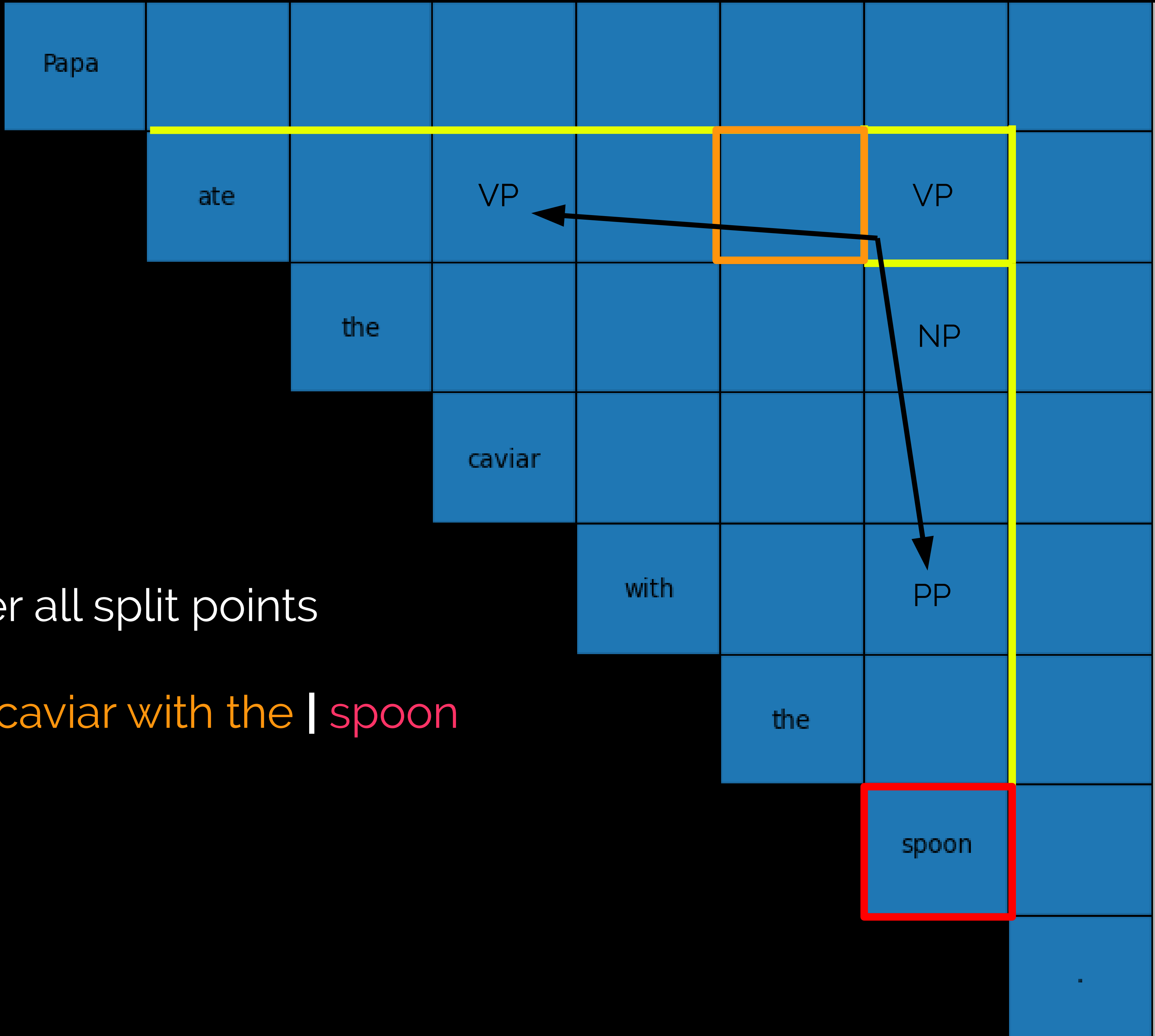

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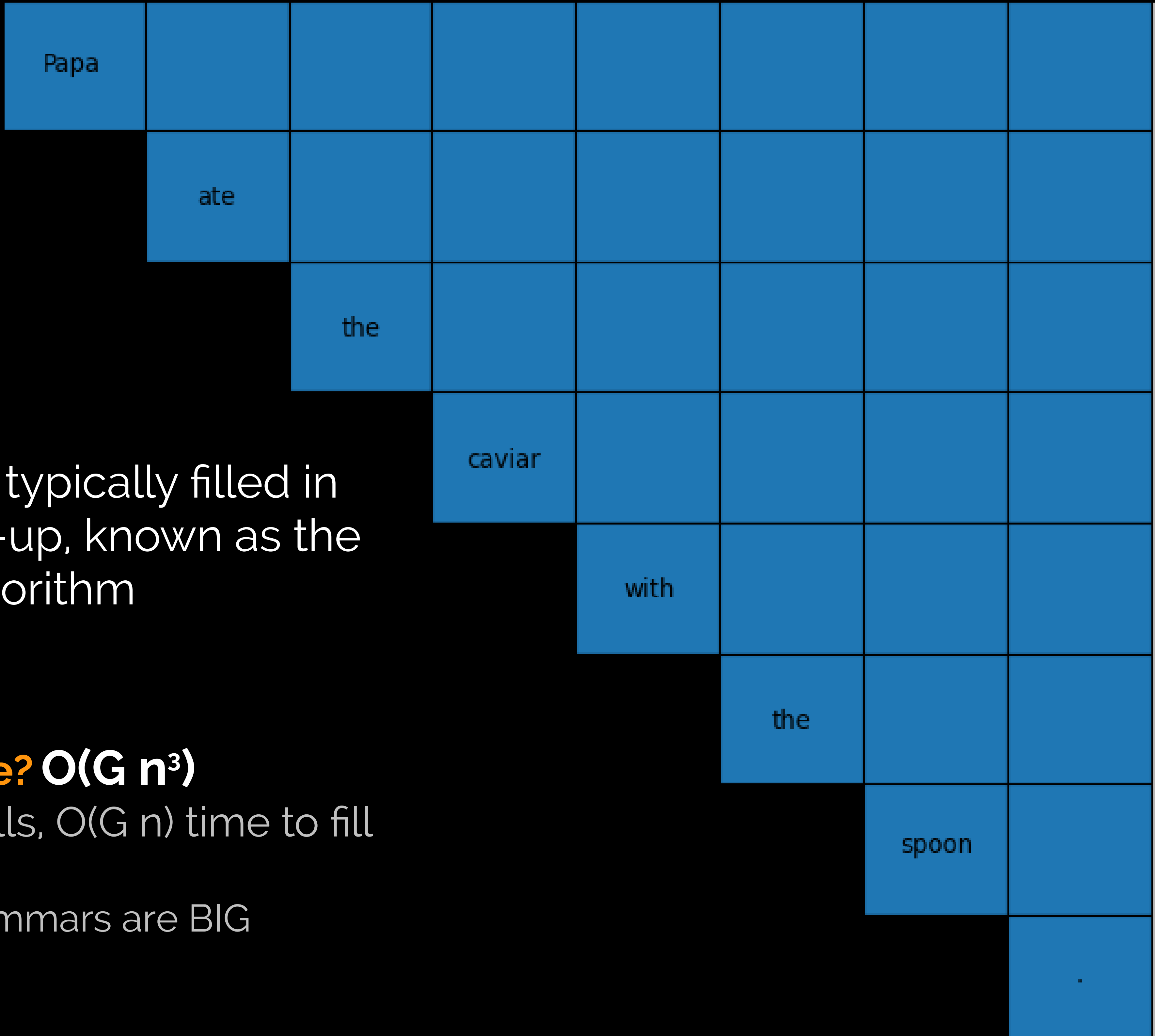


Chart is typically filled in bottom-up, known as the CKY algorithm

Runtime? $O(G\ n^3)$

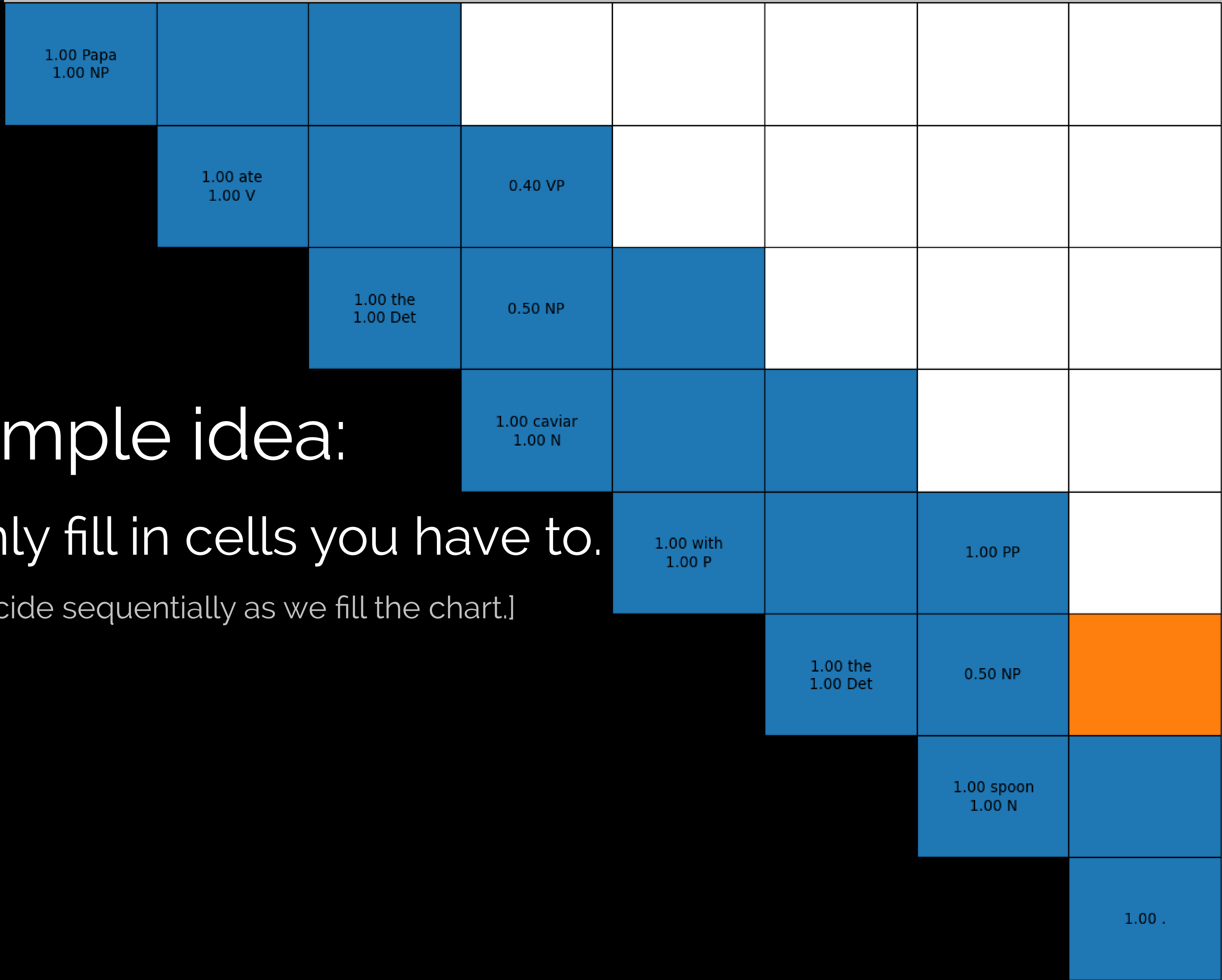
$O(n^2)$ cells, $O(G\ n)$ time to fill

Real grammars are BIG

Simple idea:

Only fill in cells you have to.

[Decide sequentially as we fill the chart.]



1.00 Papa 1.00 NP							
	1.00 ate 1.00 V		0.40 VP				
		1.00 the 1.00 Det	0.50 NP				
			1.00 caviar 1.00 N				
				1.00 with 1.00 P		1.00 PP	
					1.00 the 1.00 Det	0.50 NP	
						1.00 spoon 1.00 N	
							1.00 .

Simple idea:

Only fill in cells you have to.

Use a classifier

If $\vec{\theta}^{\intercal} f(x) < 0$ **then** skip

else fill it in

What features?

Span classification: Bodenstab (2012)

Simple idea:

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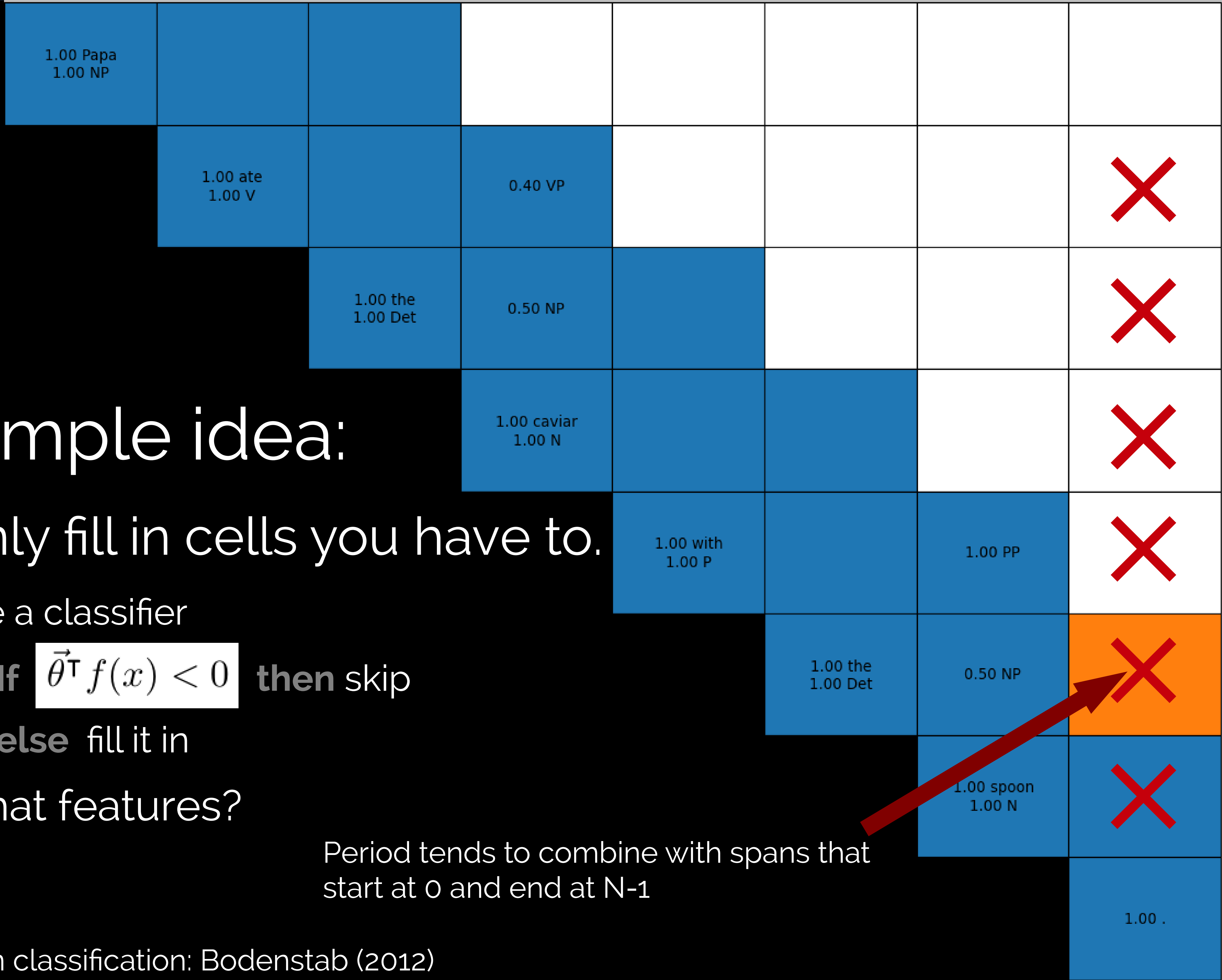
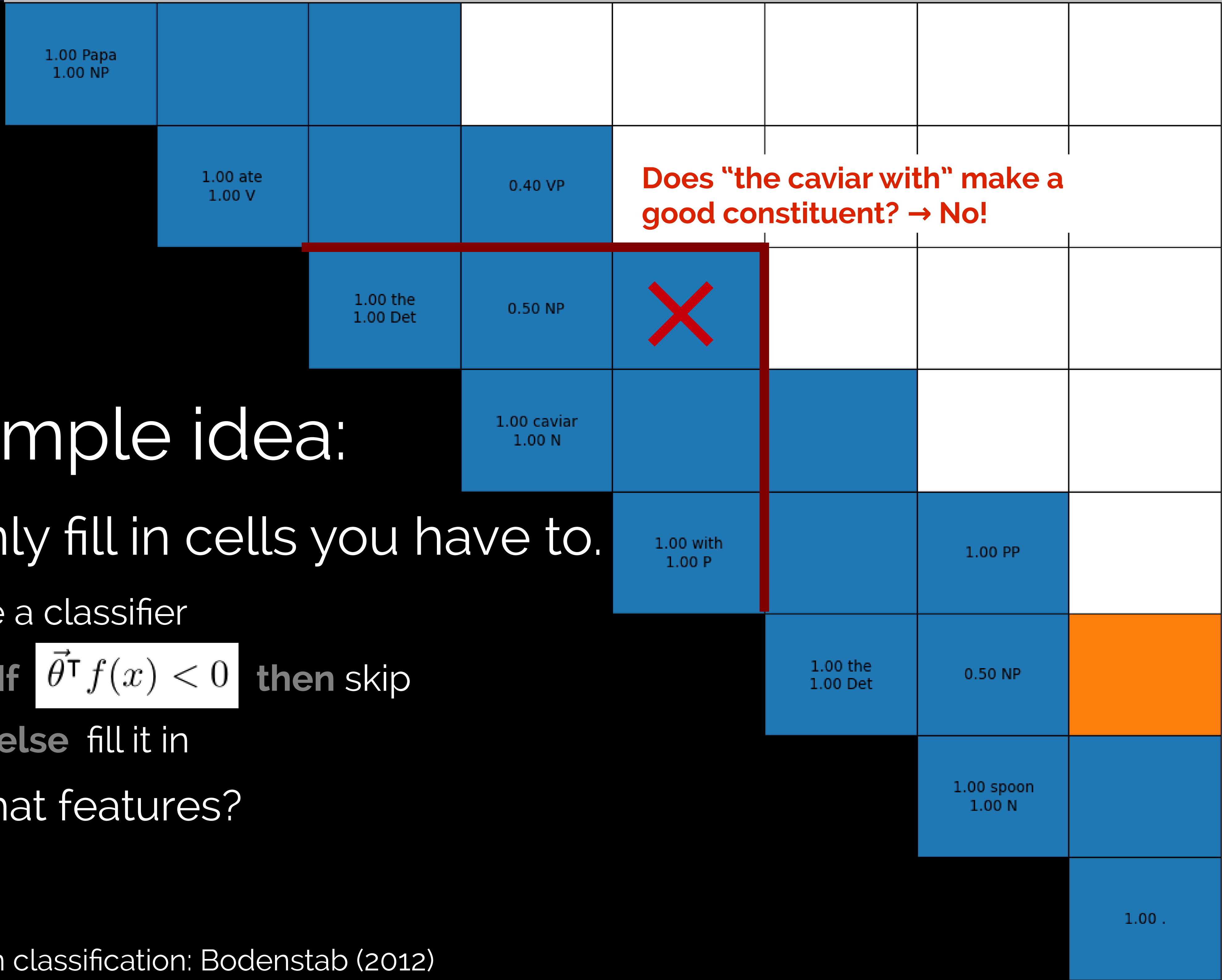


Period tends to combine with spans that start at 0 and end at N-1

Span classification: Bodenstab (2012)



Simple idea:

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How to train?

1.00 Papa 1.00 NP			1.00 S			1.00 S 1.00 S	1.00 S 1.00 S
	1.00 ate 1.00 V		0.40 VP			0.40 VP 0.10 VP	
		1.00 the 1.00 Det	0.50 NP			0.12 NP	
			1.00 caviar 1.00 N				
				1.00 with 1.00 P		1.00 PP	
					1.00 the 1.00 Det	0.50 NP	
						1.00 spoon 1.00 N	
							1.00 .

How to train?

Don't prune the **gold** parse

Everything else → negative example

(Don't prune width=1 or n, always want those.)

1.00 Papa 1.00 NP			1.00 S			1.00 S 1.00 S	1.00 S 1.00 S
	1.00 ate 1.00 V		0.40 VP			0.40 VP 0.10 VP	
		1.00 the 1.00 Det	0.50 NP			0.12 NP	
			1.00 caviar 1.00 N				
				1.00 with 1.00 P		1.00 PP	
					1.00 the 1.00 Det	0.50 NP	
						1.00 spoon 1.00 N	
							1.00 .

How to train?

Don't prune the **gold** parse

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How to train?

Don't prune
the **gold** parse

~~Everything else → negative example~~
too hard to learn.

1.00 Papa 1.00 NP			1.00 S			1.00 S 1.00 S	1.00 S 1.00 S
	1.00 ate 1.00 V		0.40 VP			0.40 VP 0.10 VP	
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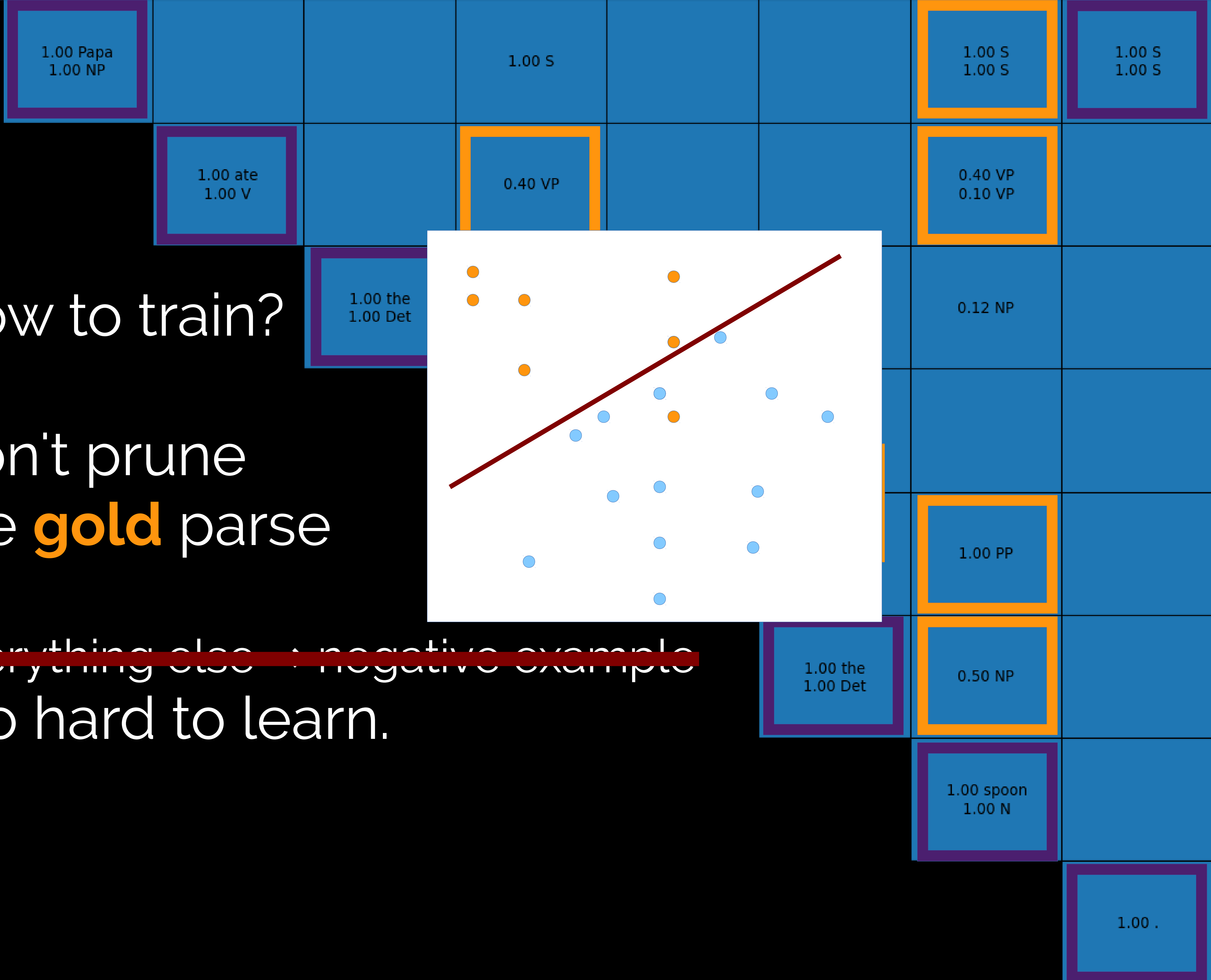

How to train?

Don't prune
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1.00 NP

1.00 S

1.00 S
1.00 S

1.00 S
1.00 S

1.00 ate
1.00 V

0.40 VP

0.40 VP
0.10 VP

1.00 the
1.00 Det

0.12 NP

1.00 PP

1.00 the
1.00 Det

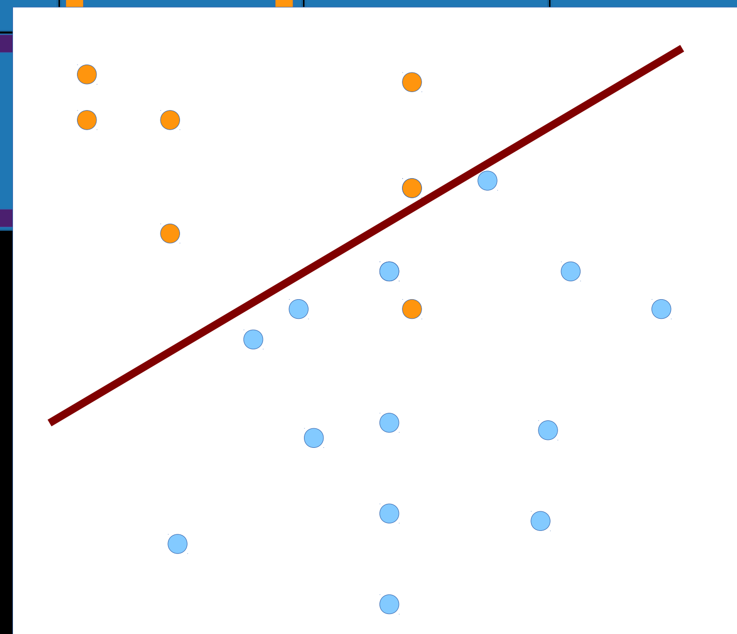
0.50 NP

1.00 spoon
1.00 N

1.00 .

How to train?

Don't prune
the **gold** parse



~~Everything else → negative example~~
too hard to learn.

If we don't prune, it only
hurts runtime a bit

1.00 Papa
1.00 NP

1.00 S

1.00 S
1.00 S

1.00 S
1.00 S

1.00 ate
1.00 V

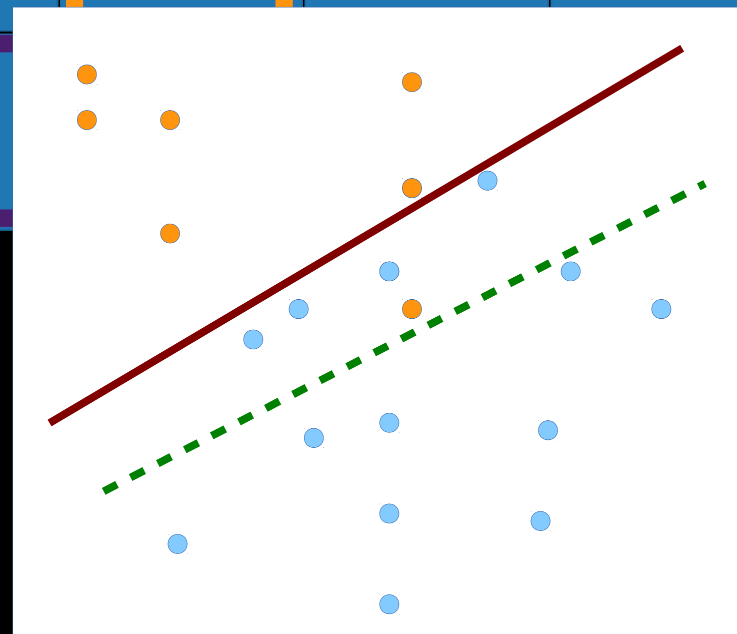
0.40 VP

0.40 VP
0.10 VP

How to train?

1.00 the
1.00 Det

0.12 NP



Don't prune the **gold** parse

1.00 PP

1.00 the
1.00 Det

0.50 NP

1.00 spoon
1.00 N

If we don't prune, it only hurts runtime a bit → **asymmetric loss**

penalize false pos/neg differently

1.00 .

How to train?

Try a bunch of asymmetric penalties

→ Speed-accuracy tradeoff
→ Works pretty well
(Bodenstab, 2012)

What's missing?

What's missing?

- Unmodeled interactions

  Fails to capture end-to-end performance.

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- Requires labeling
  - Doesn't consider other "good" parses
  - What's the best labeling to use?

What's missing?

- Unmodeled interactions

  Fails to capture end-to-end performance.

- Requires labeling
  - Doesn't consider other "good" parses
  - What's the best labeling to use?
- Limits expressiveness of features

  Doesn't support dynamic features, e.g., looking the parse chart.

Our Approach

Global objective

$$\text{reward} = \text{accuracy} - \lambda \ \text{runtime}$$

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Accuracy and runtime
of the **end-to-end** system

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Preferably
deterministic
functions
(not seconds)

Global objective

Tradeoff parameter
(exchange rate)

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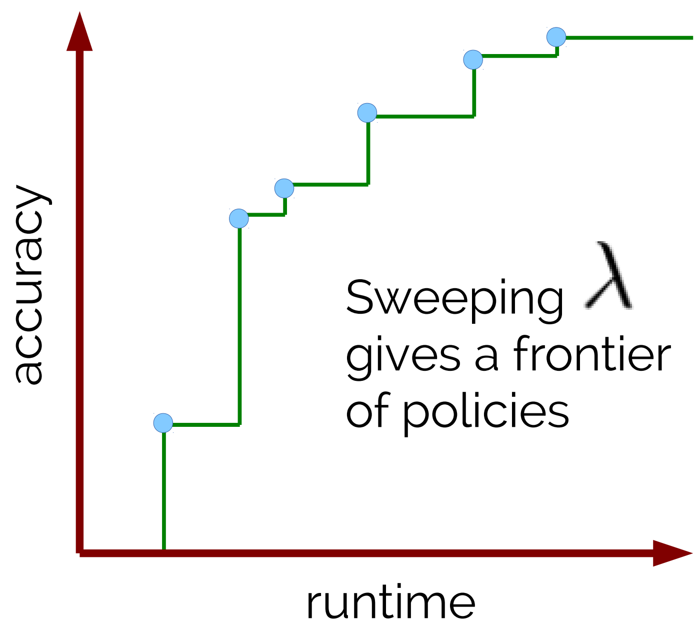
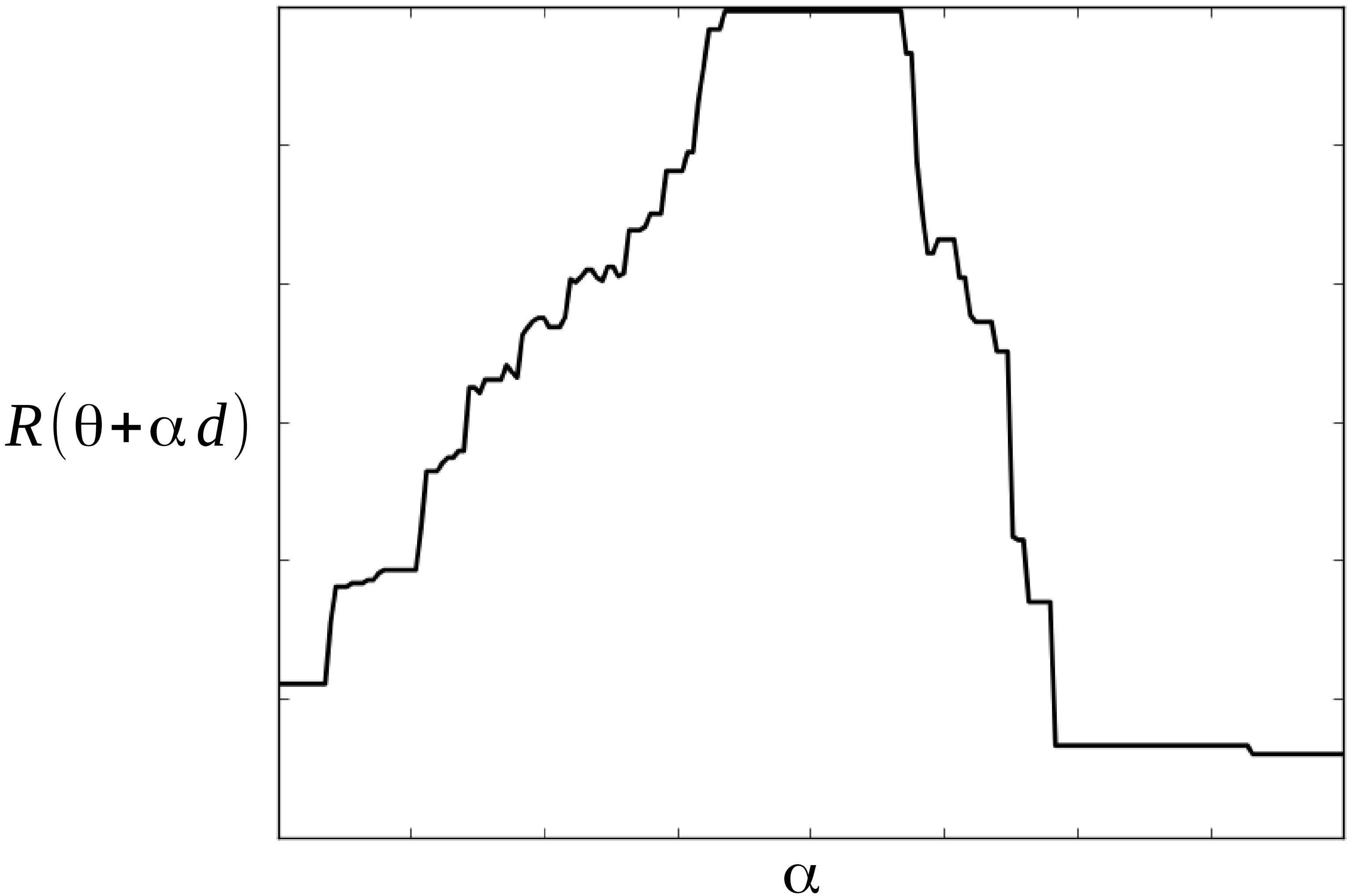


Sweeping λ
gives a frontier
of policies

How to train?

Hard to optimize

Cross-section of reward along a random direction, d



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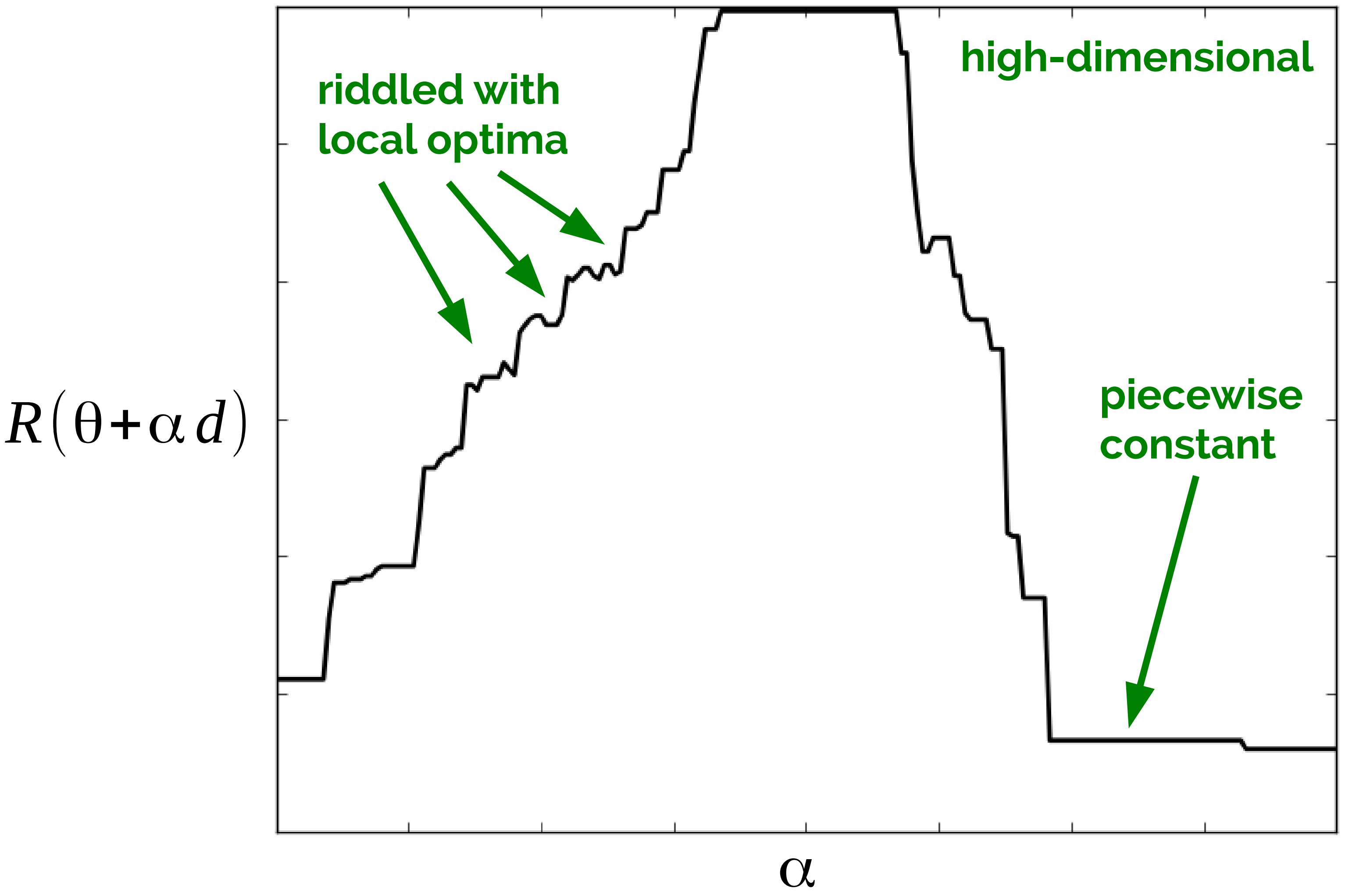

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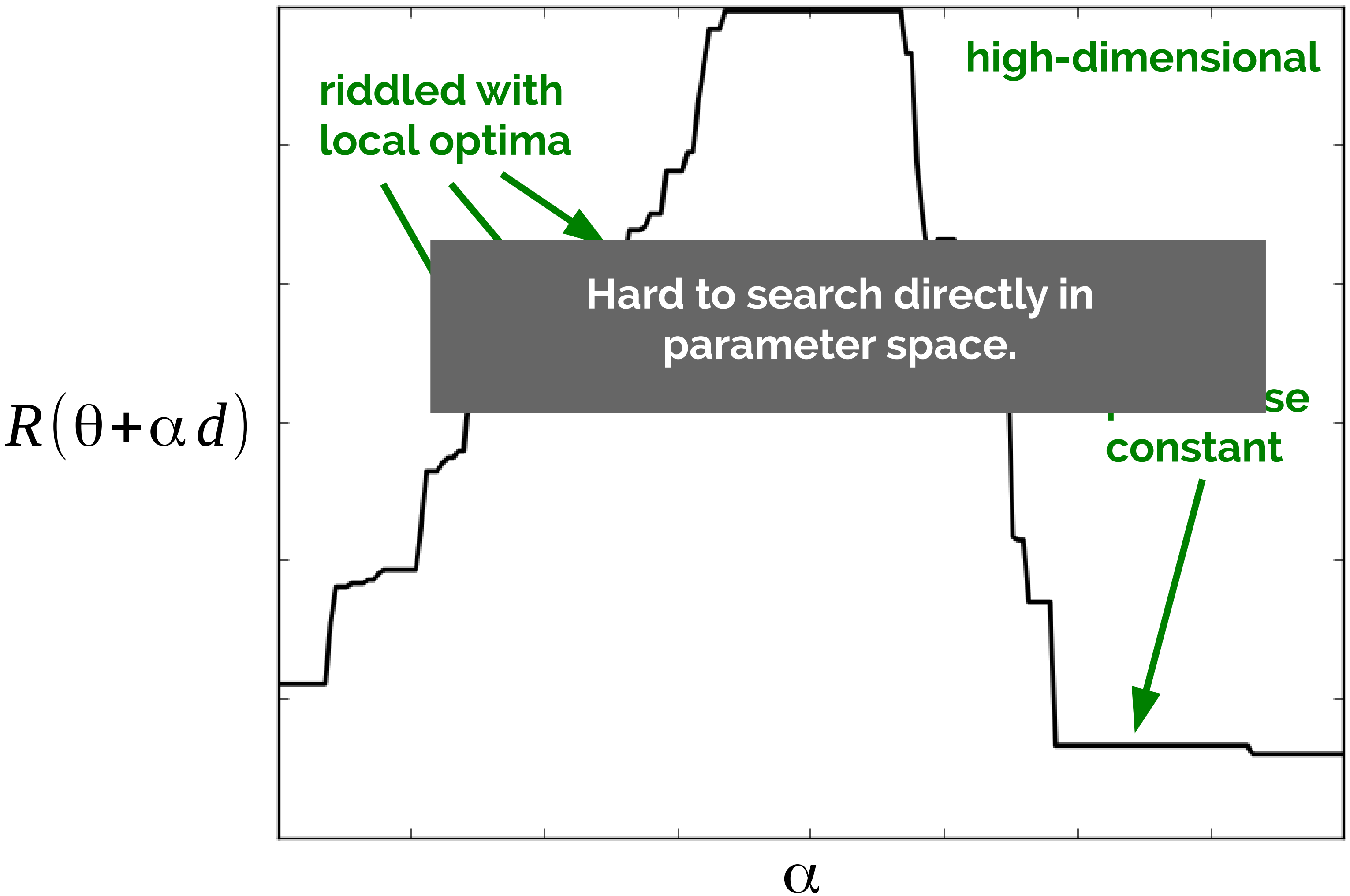

Hard to search directly in parameter space.

Approximate policy iteration

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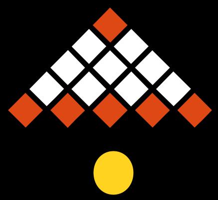

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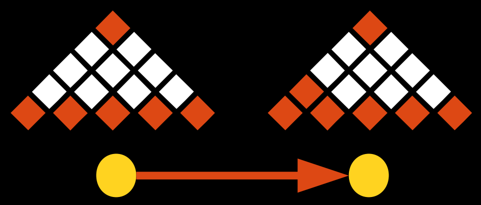

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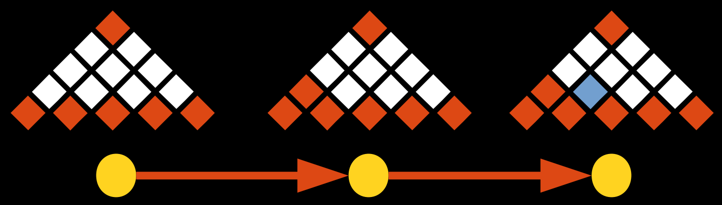

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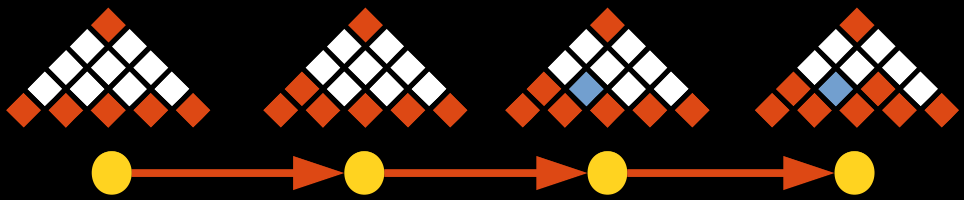

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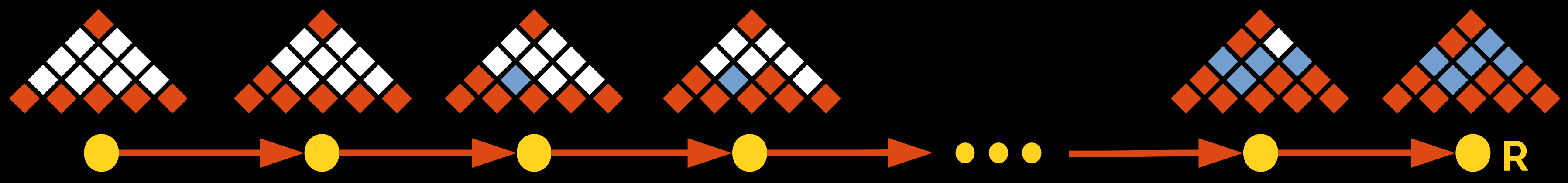

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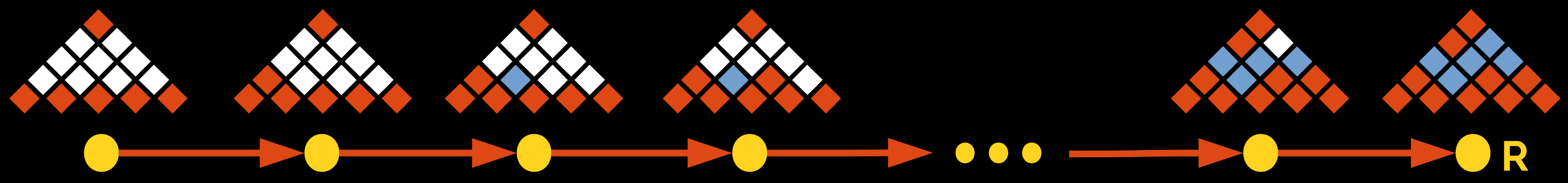
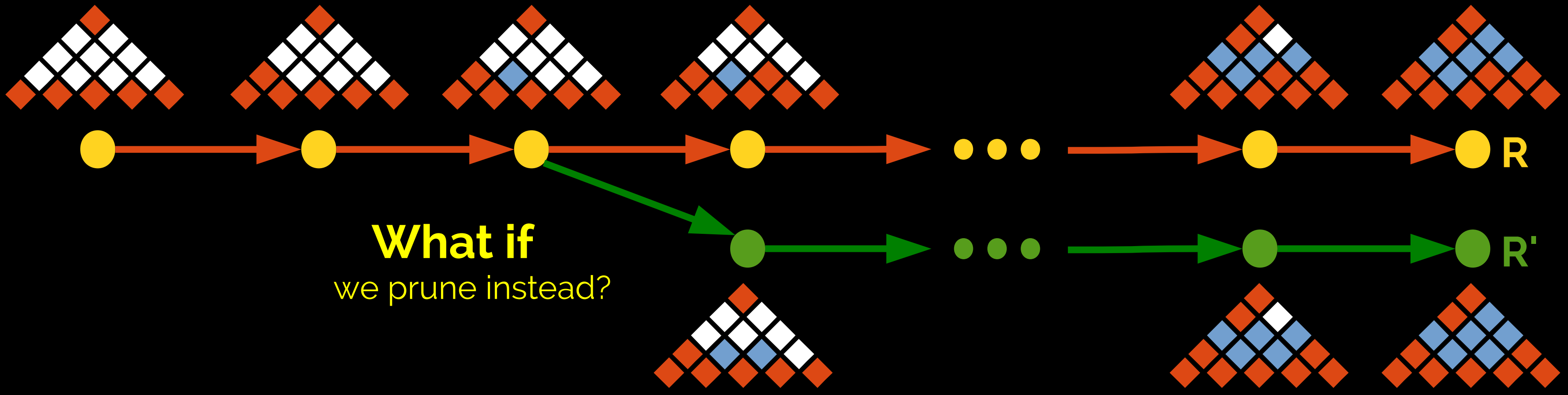


What if
we prune instead?

Approximate policy iteration



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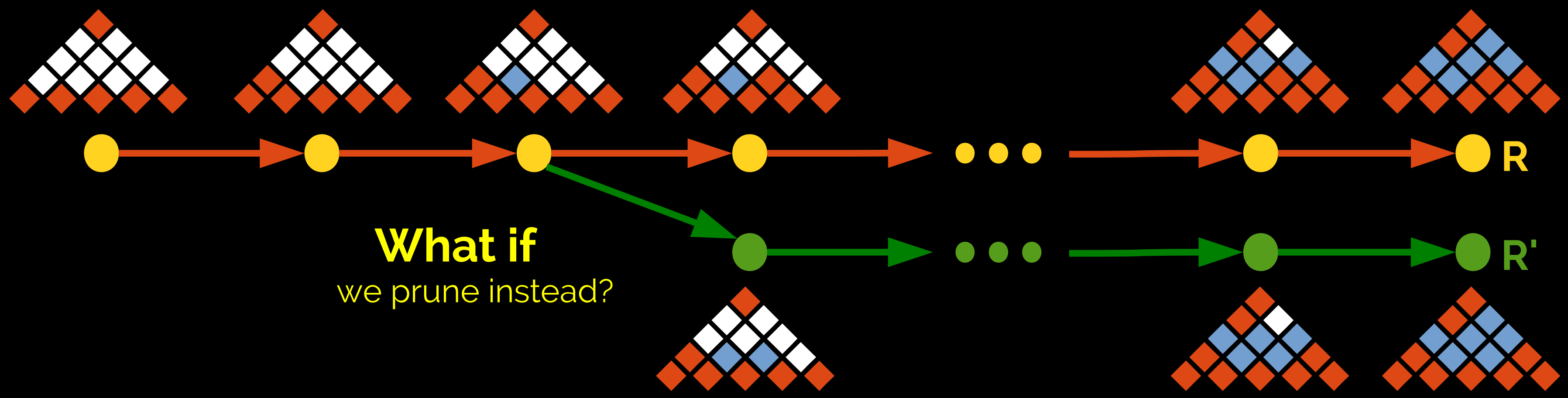
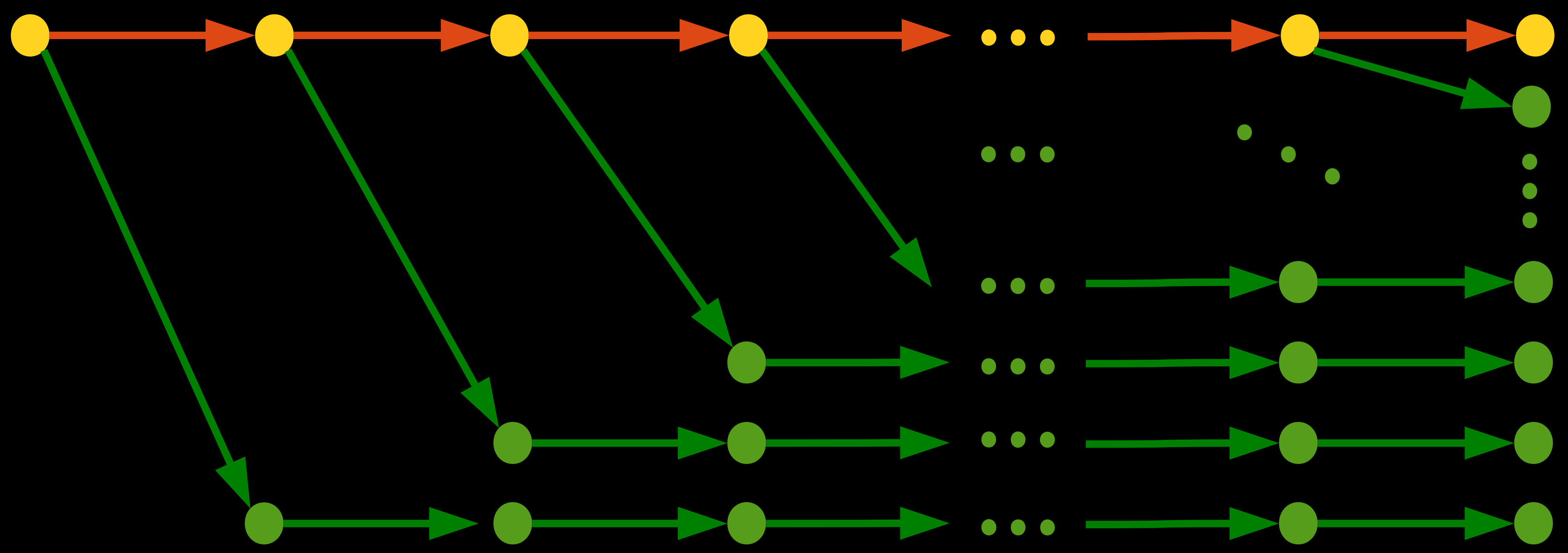


Classification example:
label: better action **R>R'**
weight: **|R – R'|**

Approximate policy iteration



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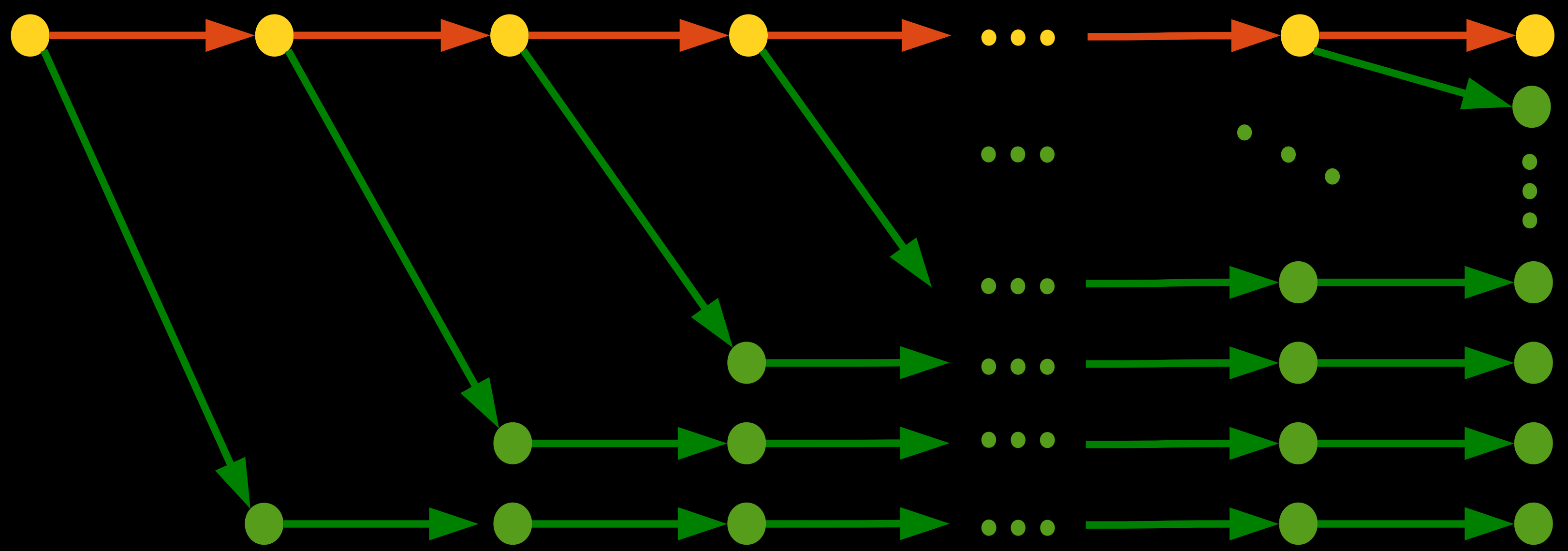
Try alternative actions at each position

Update policy

Approximate policy iteration



Classification example:
label: better action **R>R'**
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Update policy

SEARN (Daumé+,2009)
LOLS (Chang+,2015)

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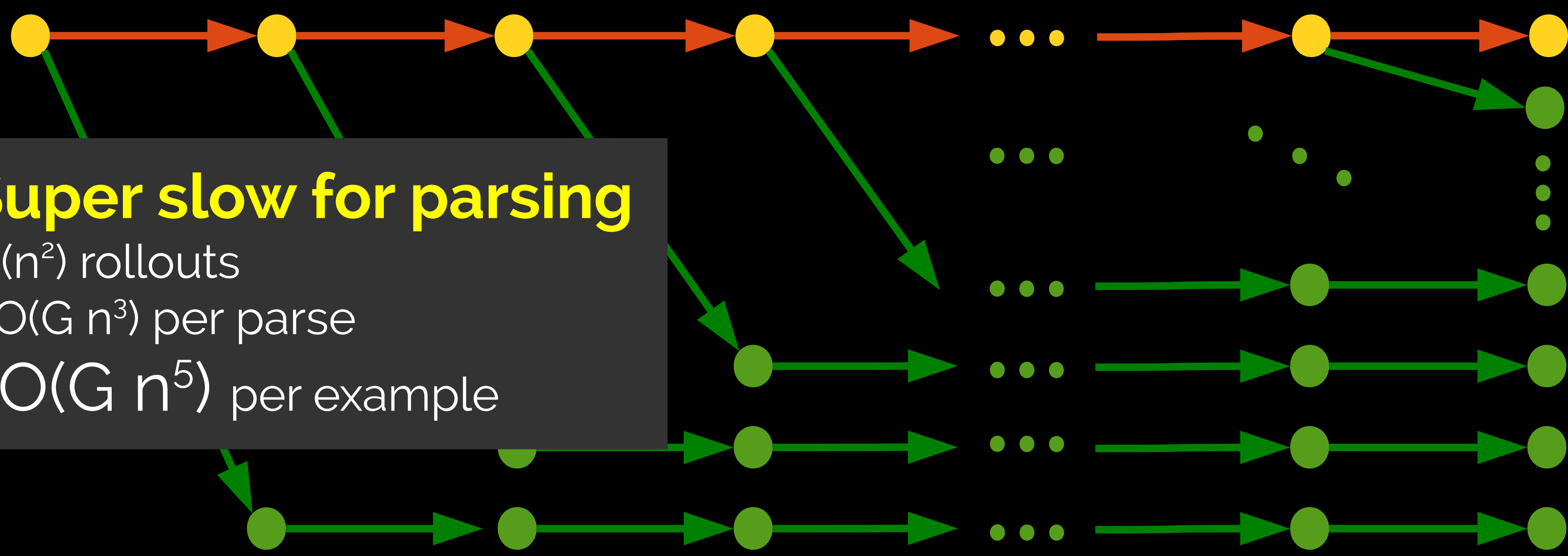

Super slow for parsing
$O(n^2)$ rollouts
$* \; O(G\,n^3)$ per parse
$= O(G\,n^5)$ per example

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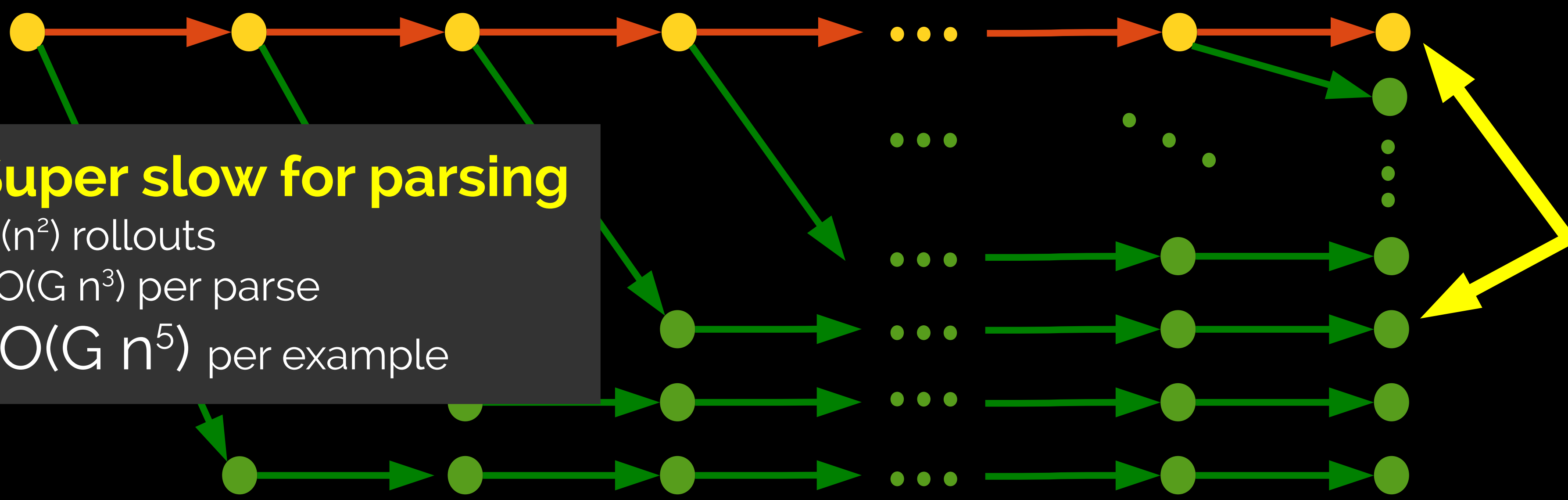


Super slow for parsing
$O(n^2)$ rollouts
* $O(G\ n^3)$ per parse
= $O(G\ n^5)$ per example

Charts are so similar!
Can we reuse work?

Try alternative actions at each position

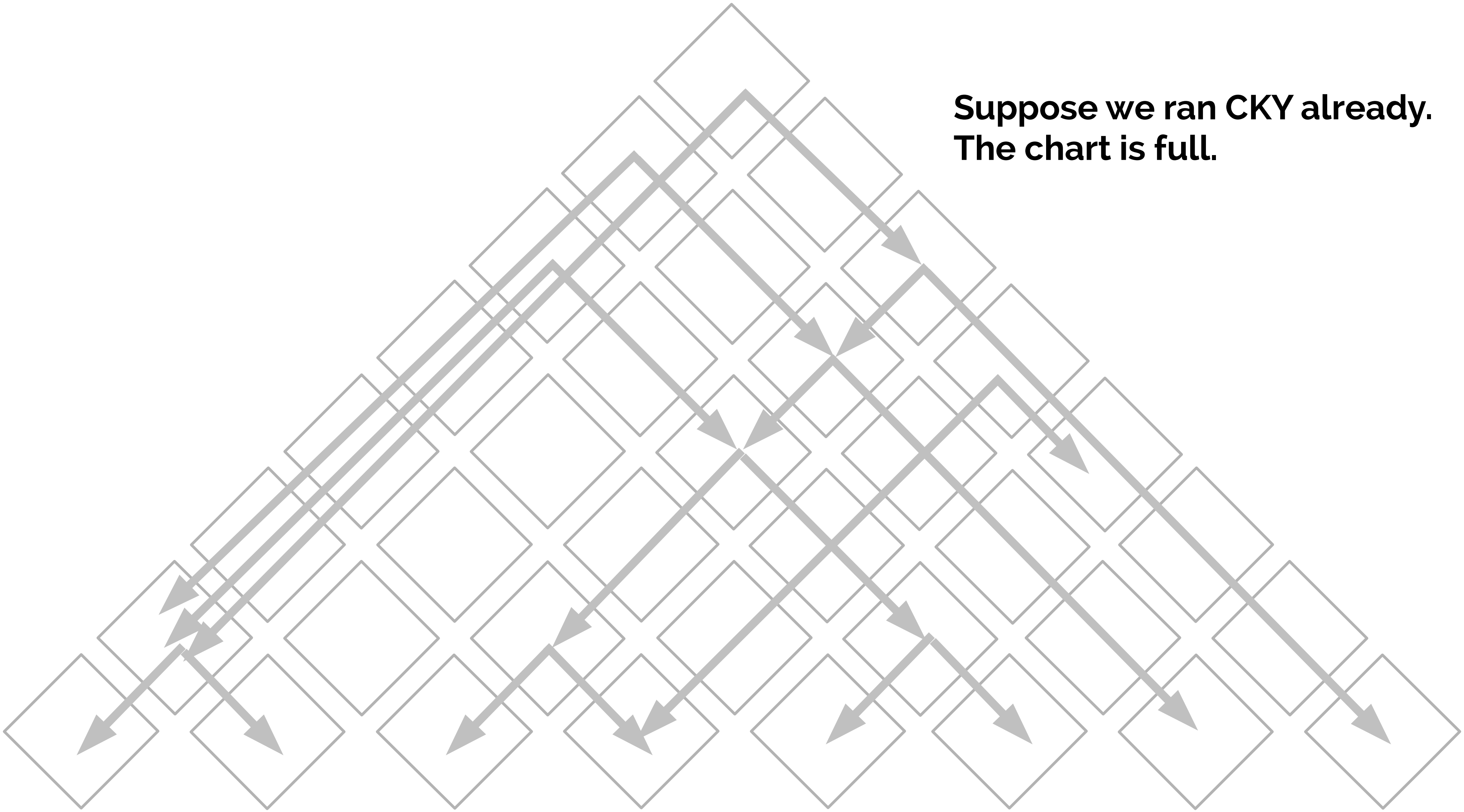
SEARN (Daumé+,2009)
LOLS (Chang+,2015)

Making learning fast

Changeprop

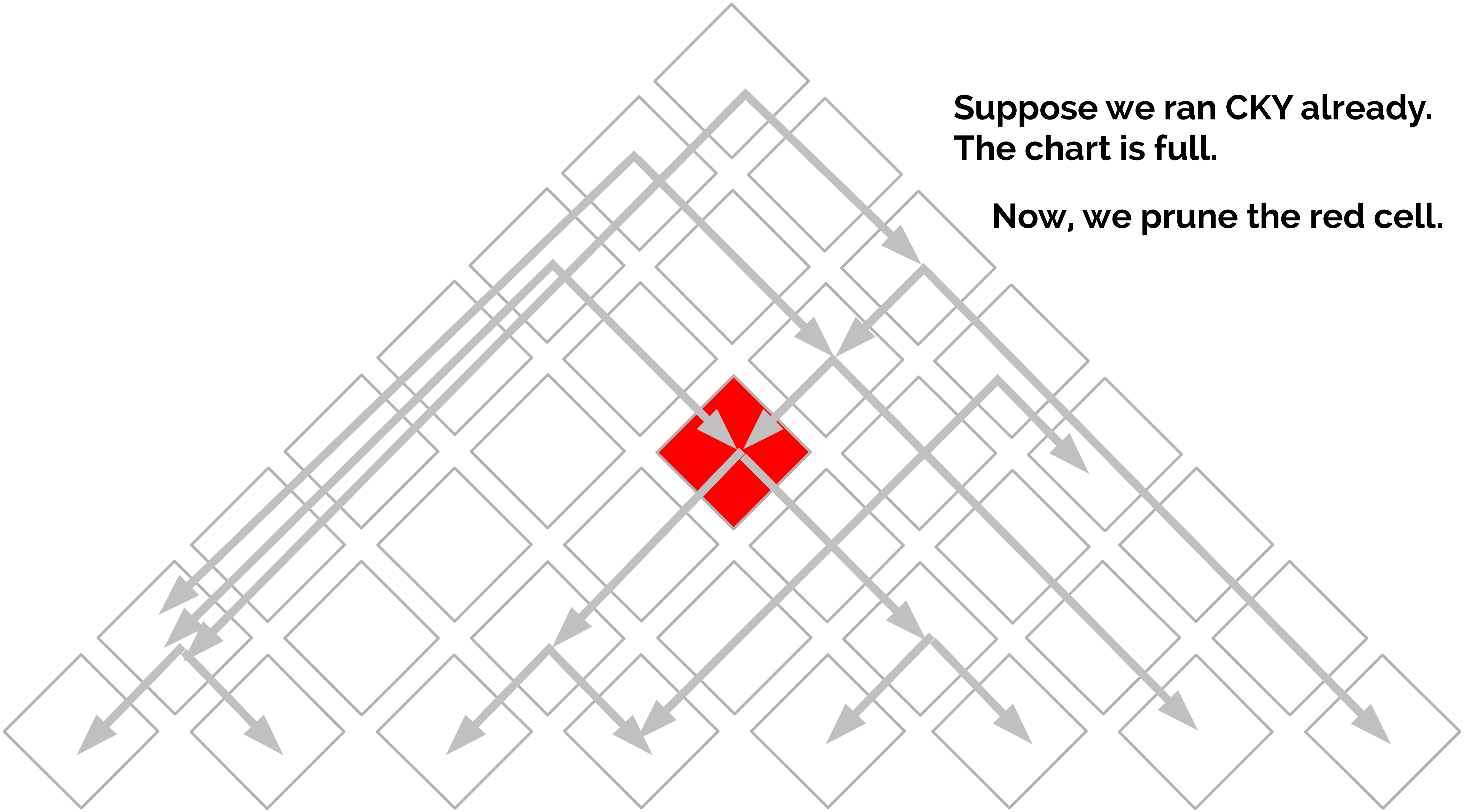
Like a Makefile for parse charts...

Changeprop



Suppose we ran CKY already.
The chart is full.

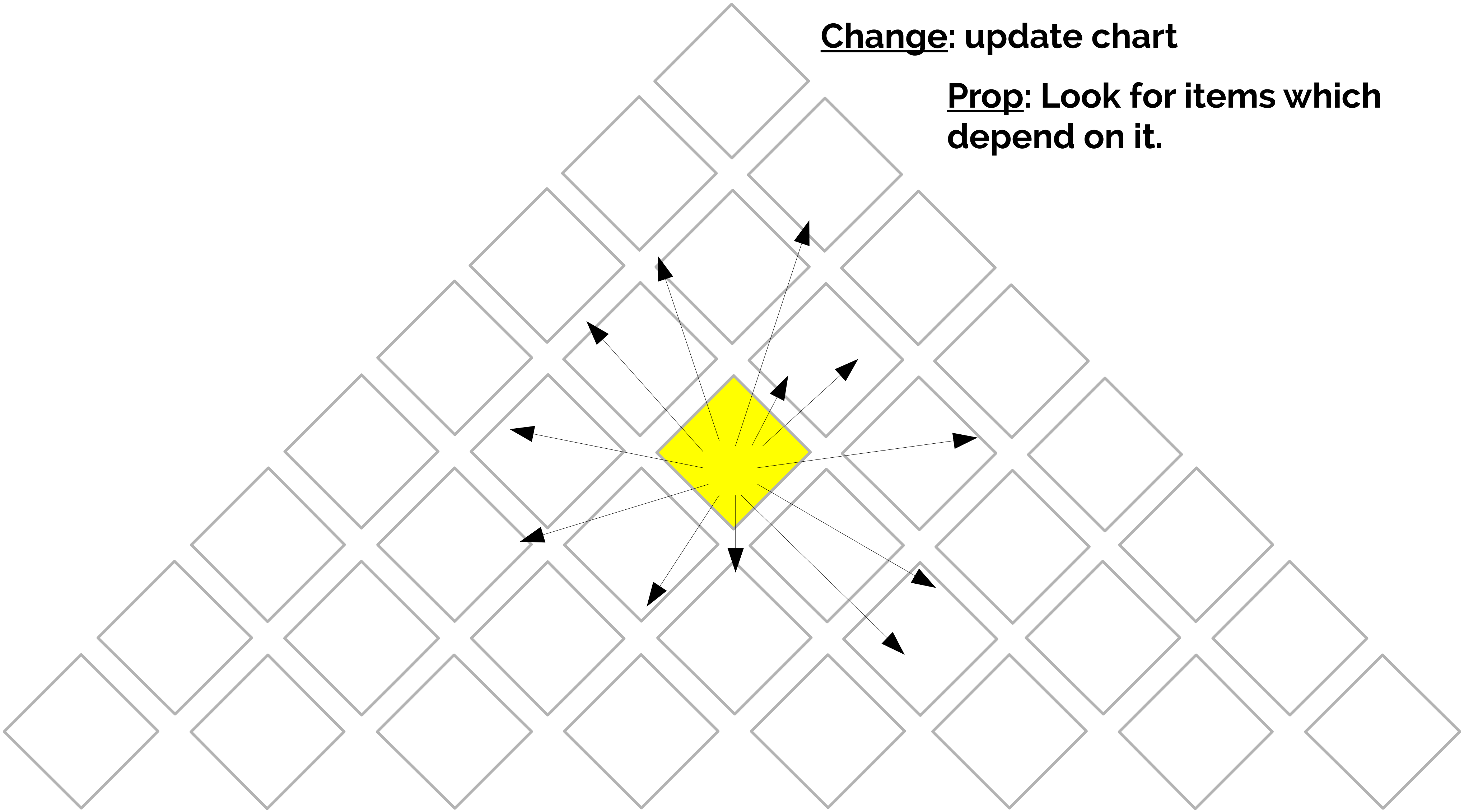
Changeprop



Suppose we ran CKY already.
The chart is full.

Now, we prune the red cell.

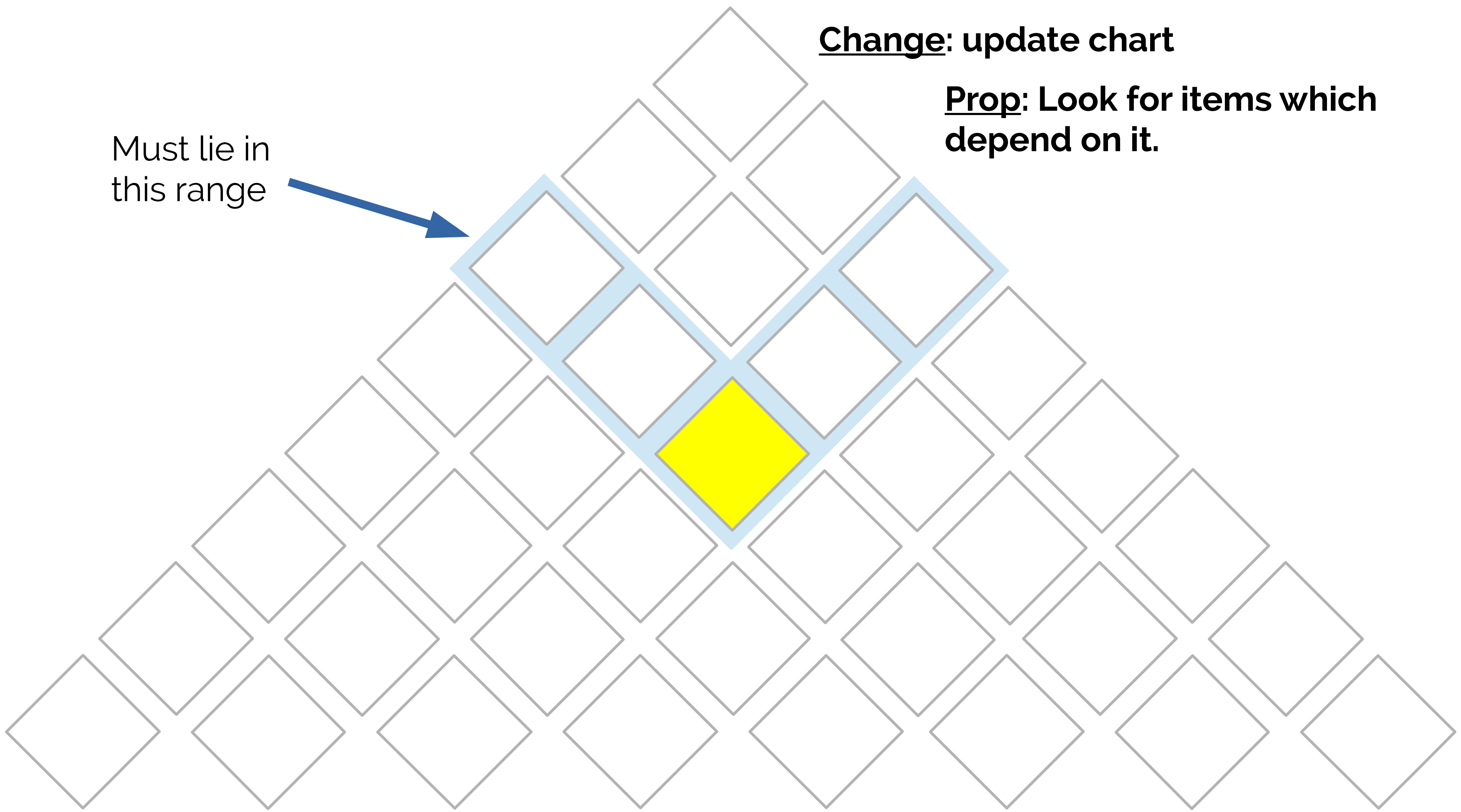
Changeprop



<u>Change</u>: update chart

<u>Prop</u>: Look for items which depend on it.

Changeprop

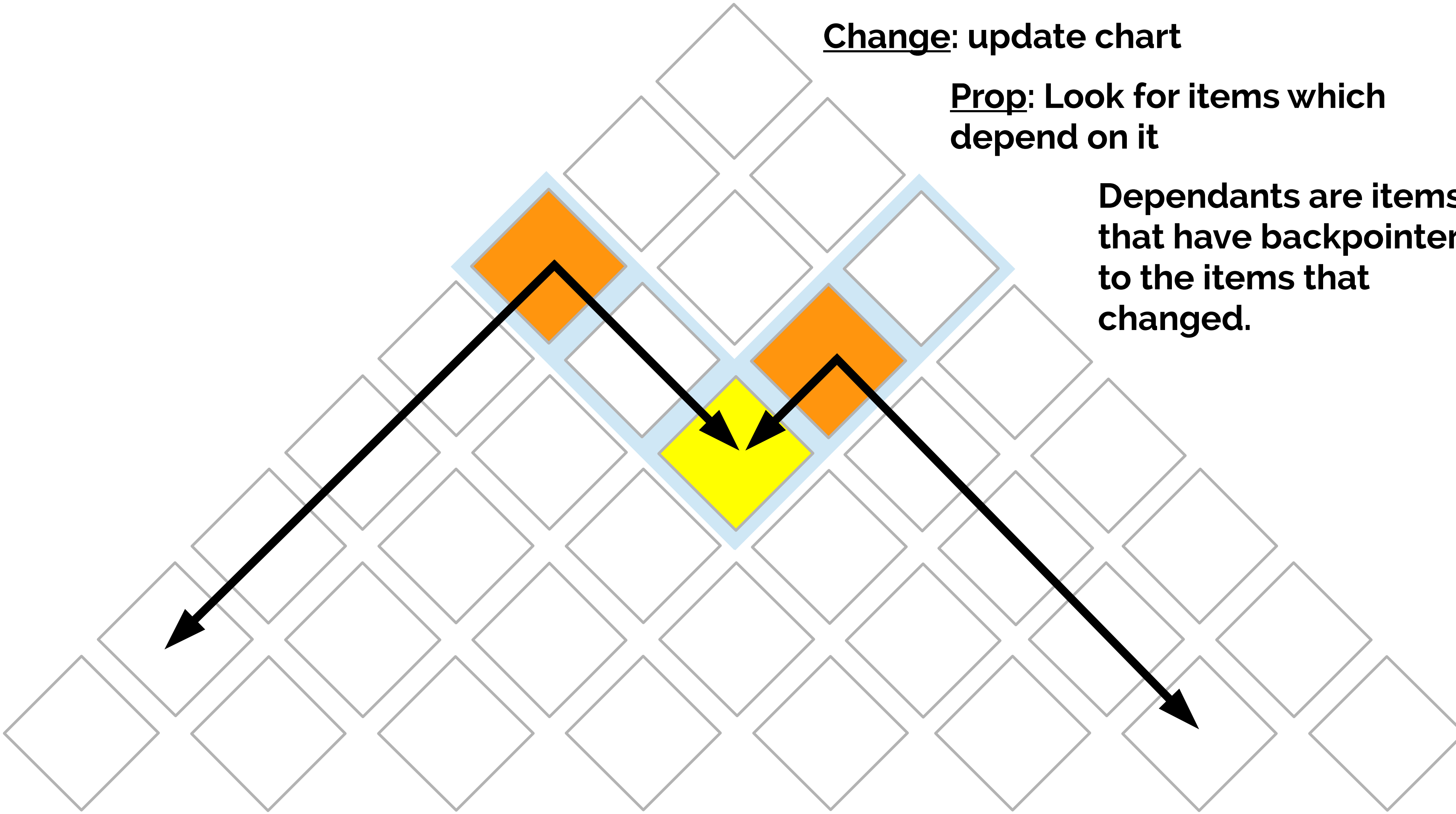

Change: update chart
Prop: Look for items which depend on it.
Must lie in this range

Changeprop

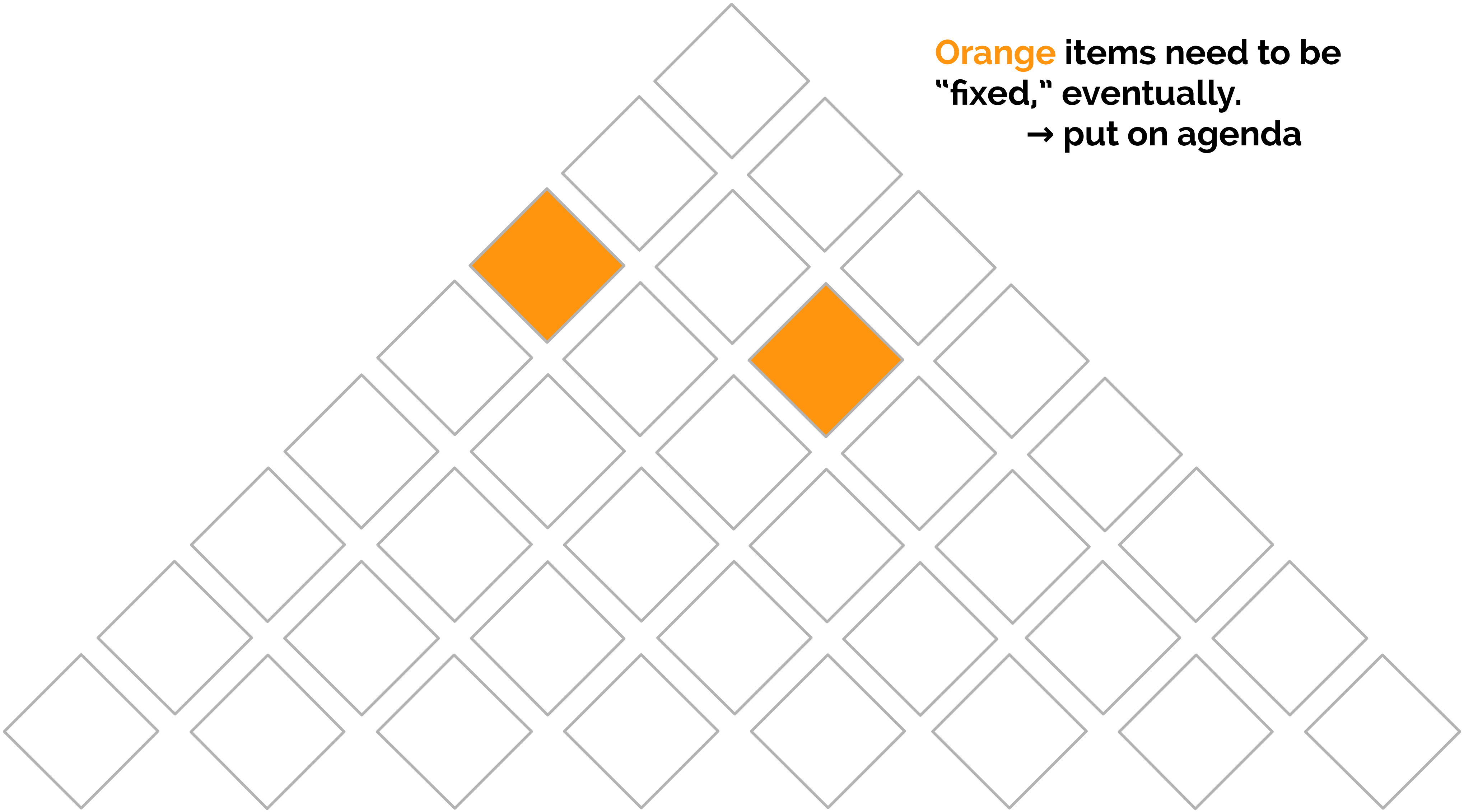
<u>Change</u>: update chart

<u>Prop</u>: Look for items which depend on it

Dependants are items that have backpointers to the items that changed.

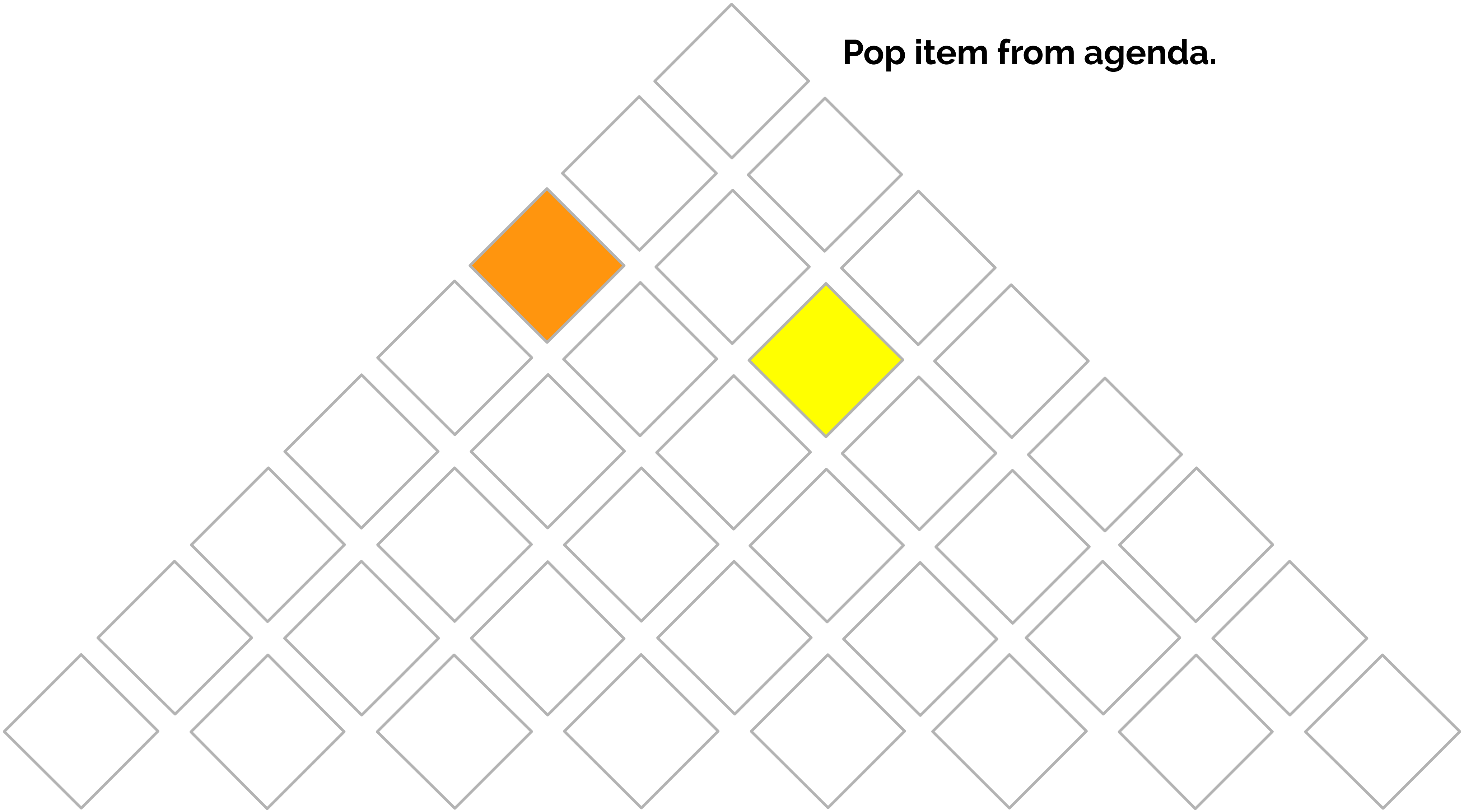


Changeprop

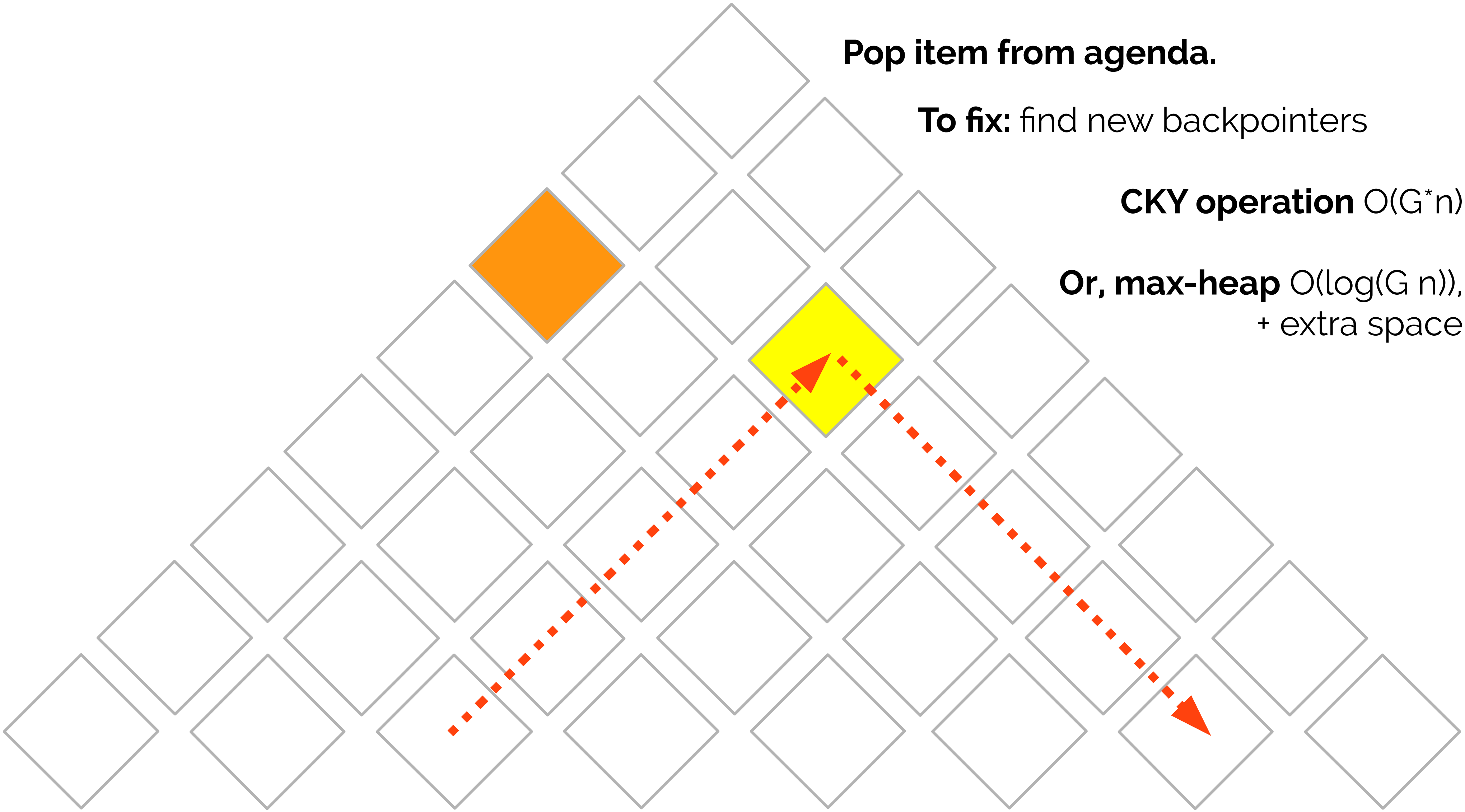


Orange items need to be "fixed," eventually.
→ put on agenda

Changeprop



Changeprop



Pop item from agenda.

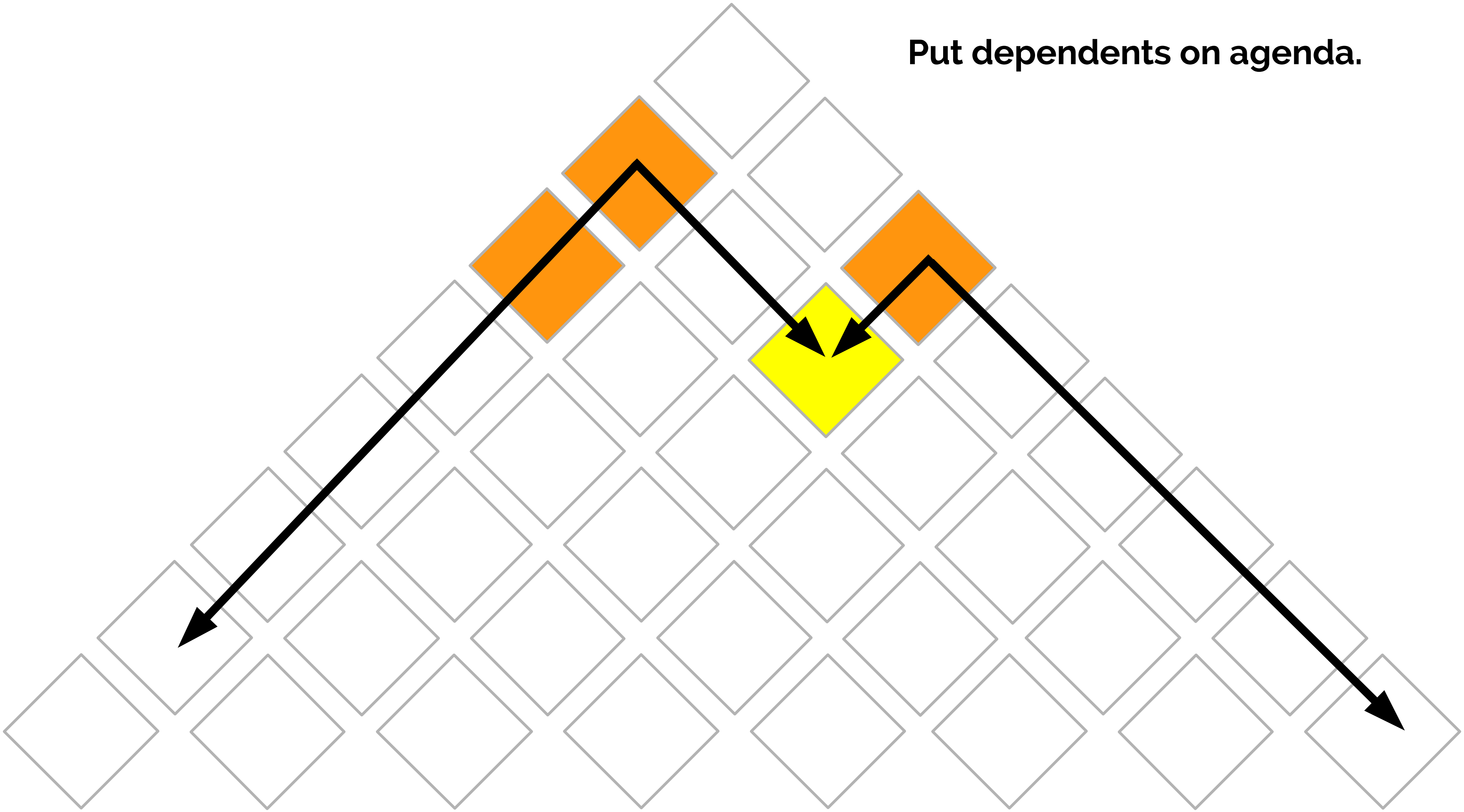
To fix: find new backpointers

CKY operation O(G*n)

Or, max-heap O(log(G n)),
+ extra space

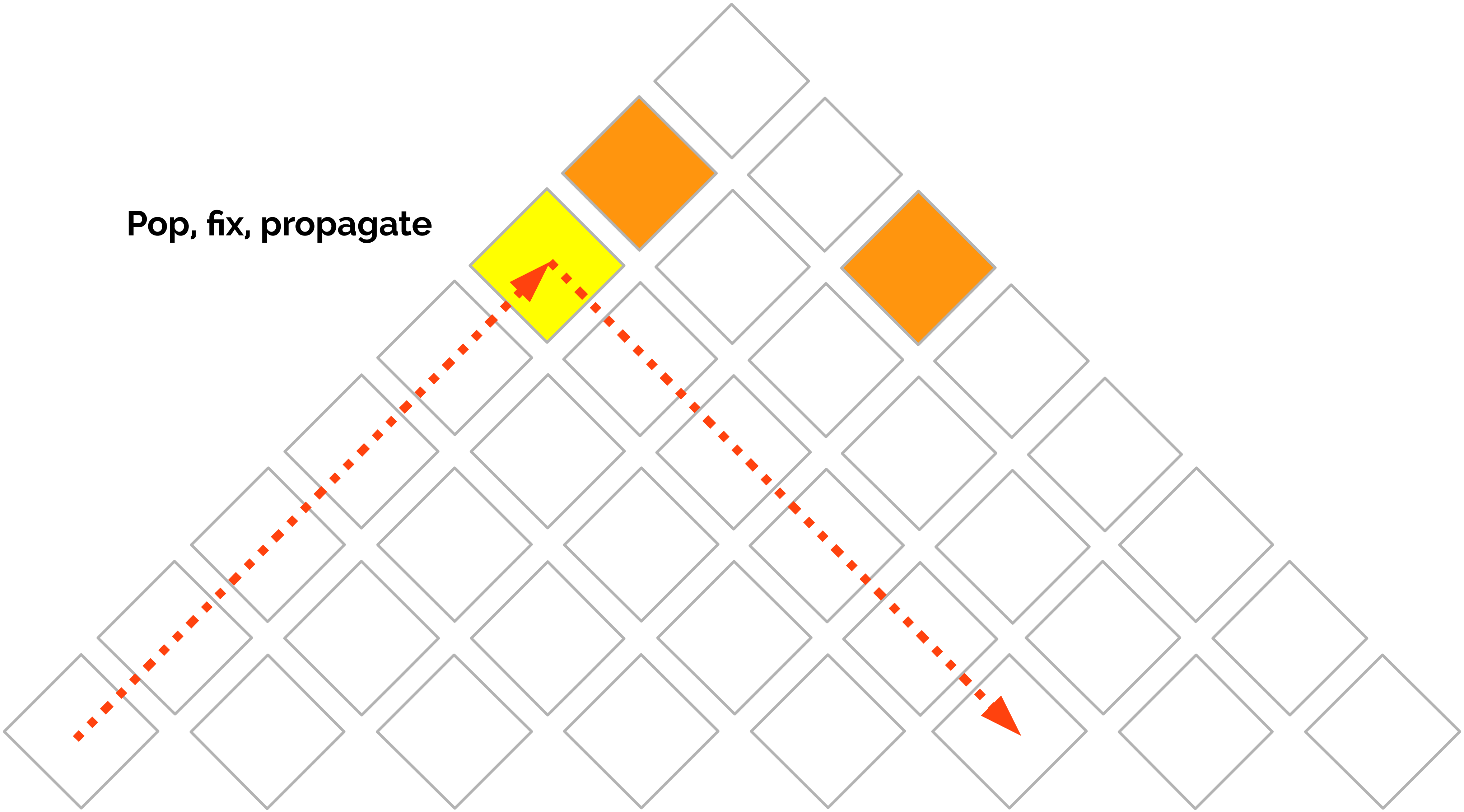
Changeprop

Put dependents on agenda.

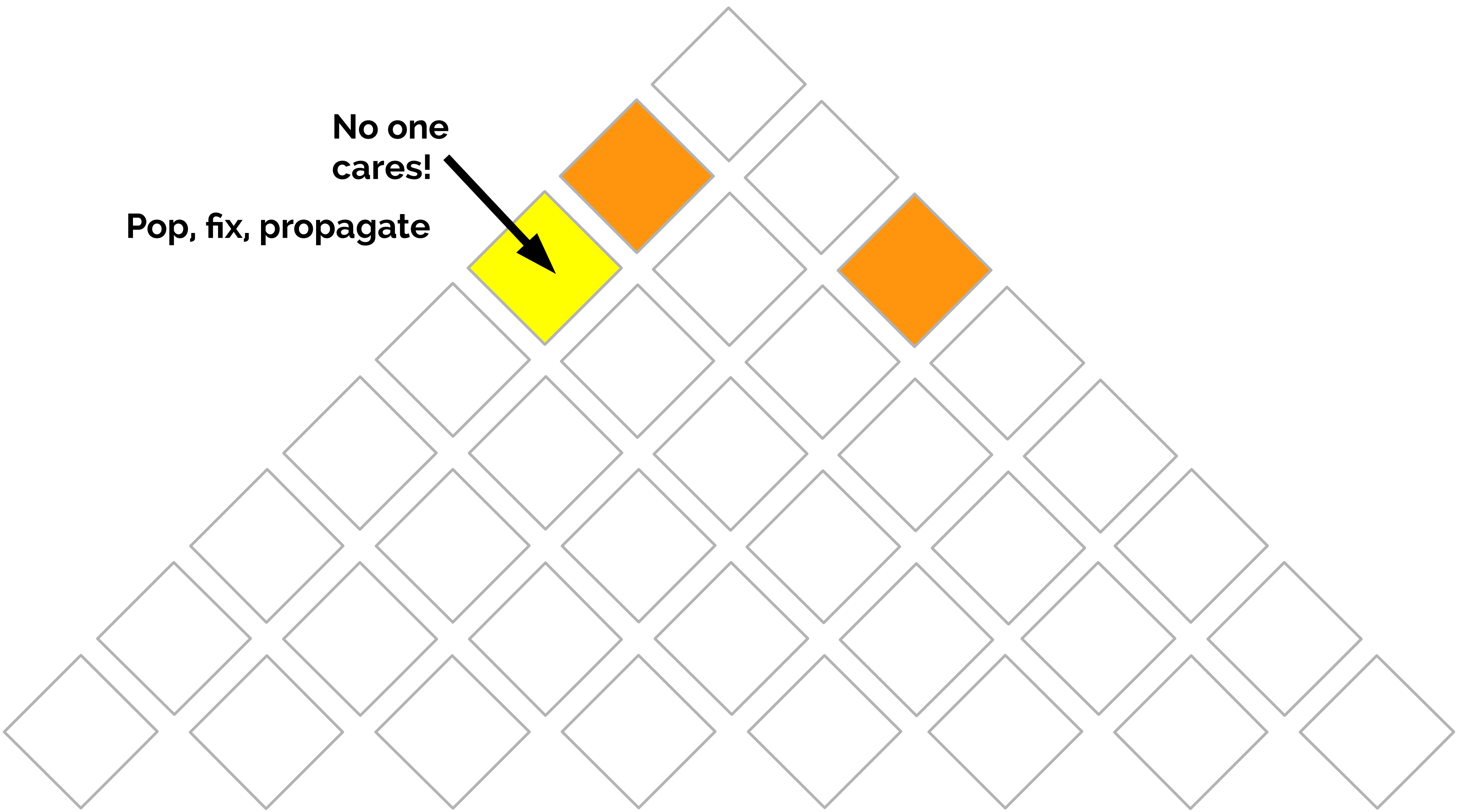


Changeprop

Pop, fix, propagate



Changeprop



Changeprop

And so on...
Until agenda is empty

Changeprop

And so on...
Until agenda is empty

Evaluate reward on converged chart

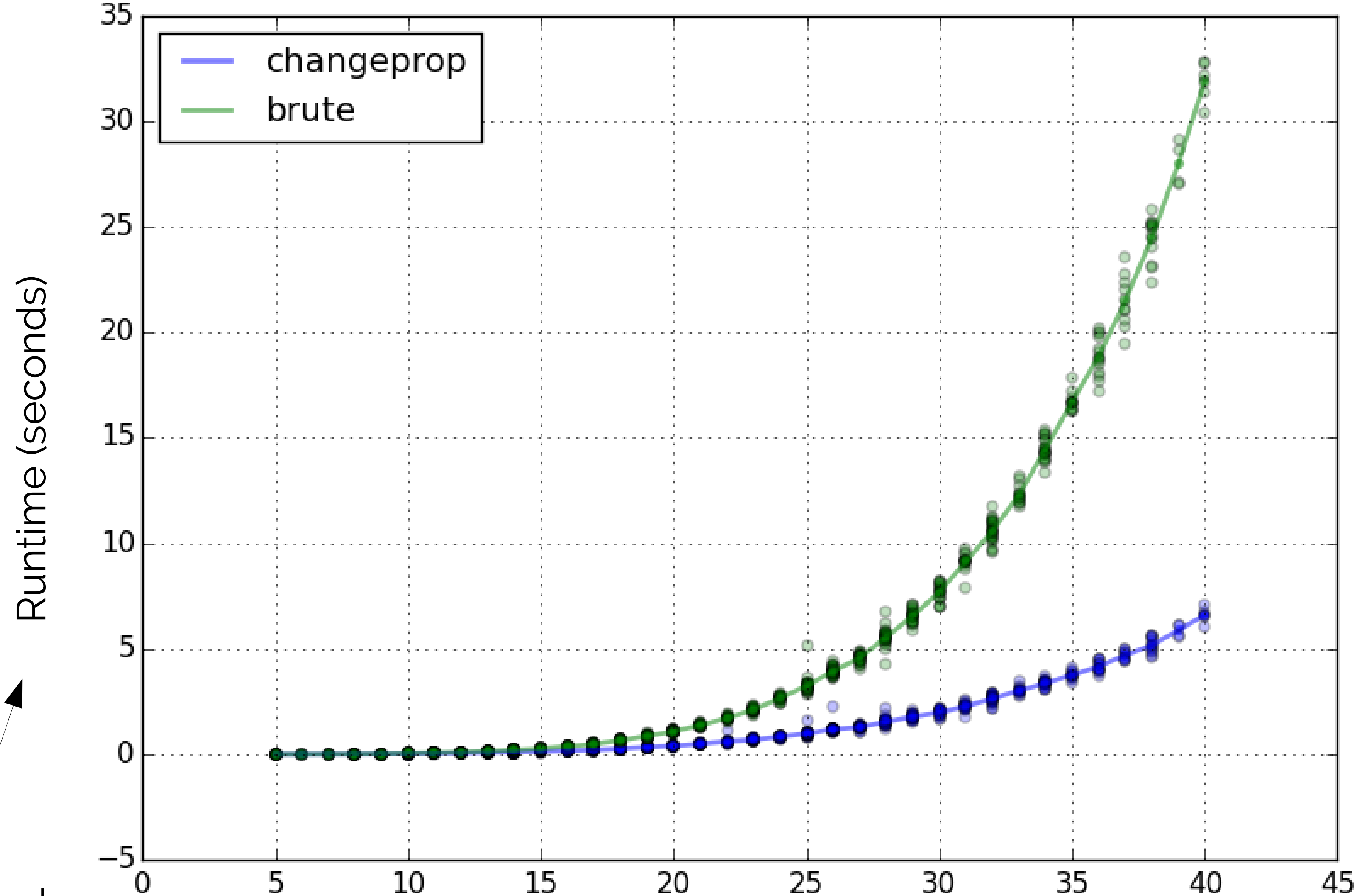
Changeprop


And so on...
Until agenda is empty
Evaluate reward on converged chart
What about unprune?

Changeprop

- Like a Makefile for parse charts → fast because changes are sparse.
- Leverages structure of underlying computation so that we can efficiently propagate updates.
- Not an asymptotic speed up, but works very well in practice.

Empirical comparison



Time to do all rollouts.

Sentence length

1K sentences, 5 < len <= 40, not much pruning

Dynamic program

Dynamic program

Rollouts are a lot like a gradient...

$$\frac{\Delta r}{\Delta \pi_j}$$

Dynamic program

Expected reward:

$$r\left(\underset{d\in D}{\operatorname{argmax}}\, p(d)\right) \approx \sum_{d\in D} r(d)\, p(d)$$

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Sample a tree from the pruned forest instead of argmax

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Differentiable: If we change one edge's value a little bit. The gradient tells us how reward changes.

$$r(\vec{k} + \varepsilon \cdot \vec{1}_e) \approx r(\vec{k}) + \varepsilon \cdot \frac{\partial r}{\partial k_e}$$

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Inaccurate for large ε

Sample a tree from the pruned forest instead of argmax

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Expected reward:

$$r = \sum_{d \in D} r(d)\, p(d)$$

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Multi-linear **(by example)**

$$f(x, y, z) = xyz$$

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$$f(x+\varepsilon, y, z) = (x+\varepsilon)\, yz$$

$$= xyz + \varepsilon\, yz$$

$$= f(x, y, z) + \varepsilon \frac{\partial f}{\partial x}$$

Now, what happens if we change just one edge?

Dynamic program

Expected reward:

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Break-up into numerator and denominator.

$$\bar{r} = \sum_{d \in D} r(d)\, \bar{p}(d) = \sum_{d \in D} r(d) \prod_{e \in d} k_e$$

$$Z = \sum_{d \in D} \prod_{e \in d} k_e$$

Now, what happens if we change just one edge?

Multi-linear function of edge weights!

Dynamic program

Expected reward:

$$r = \sum_{d \in D} r(d)\, p(d)$$

Break-up into numerator and denominator.

$$Z = \sum_{d \in D} \prod_{e \in d} k_e$$

Now, what happens if we change just one edge?

Taylor expansion works!

$$\bar{r}(\vec{k} + \varepsilon \cdot \vec{1}_e) = \bar{r}(\vec{k}) + \varepsilon \cdot \frac{\partial \bar{r}}{\partial k_e}$$

Same for Z

Quotient of separate expansions gives us exact expected reward for any perturbation.

Dynamic program

Loose ends

- Efficiently computing gradients

- Pruning affects more than one edge at a time.

- Want one-best, not expected

Dynamic program

Loose ends

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Fast algorithms for decomposable rewards,
e.g., Second-order inside-outside algorithm
(Li & Eisner,09)

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Annealing – a general trick for interpolating between expectation and maximization.

$$\lim_{\gamma \to \infty} \frac{1}{Z_\gamma} \sum_{d \in D} r(d)\, p(d)^\gamma = r\left(\operatorname{argmax}_{d \in D} p(d)\right)$$

Dynamic program

- How it works: a carefully applied Taylor expansion gives us an $O(G\,n^3 + n^2)$ algorithm.

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    Boolean version of changeprop for runtime is super fast.

Dynamic program

- How it works: a carefully applied Taylor expansion gives us an $O(G\ n^3 + n^2)$ algorithm.
- Fast and exact for decomposable reward functions
  - Accuracy :-)
  - Runtime :-(
    Boolean version of changeprop for runtime is super fast

Sorry, no benchmark plot, yet.

Experiments

TODO

- See paper for updated experimental results.

Conclusions

- Modeling end-to-end performance leads to better policies

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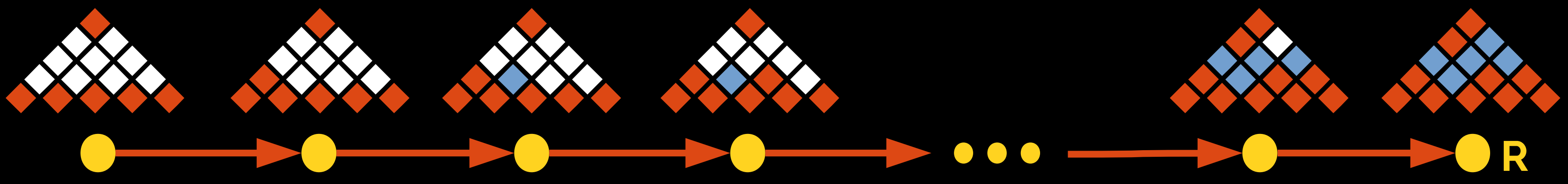
- LOLS works pretty well for training
- Training under end-to-end objective requires running inference millions of times.

  We presented efficient algorithms for repeated inference: change propagation and dynamic programming.

Thanks!



Twitter: @xtimv
Blog: http://timvieira.github.io/blog

Backup slides

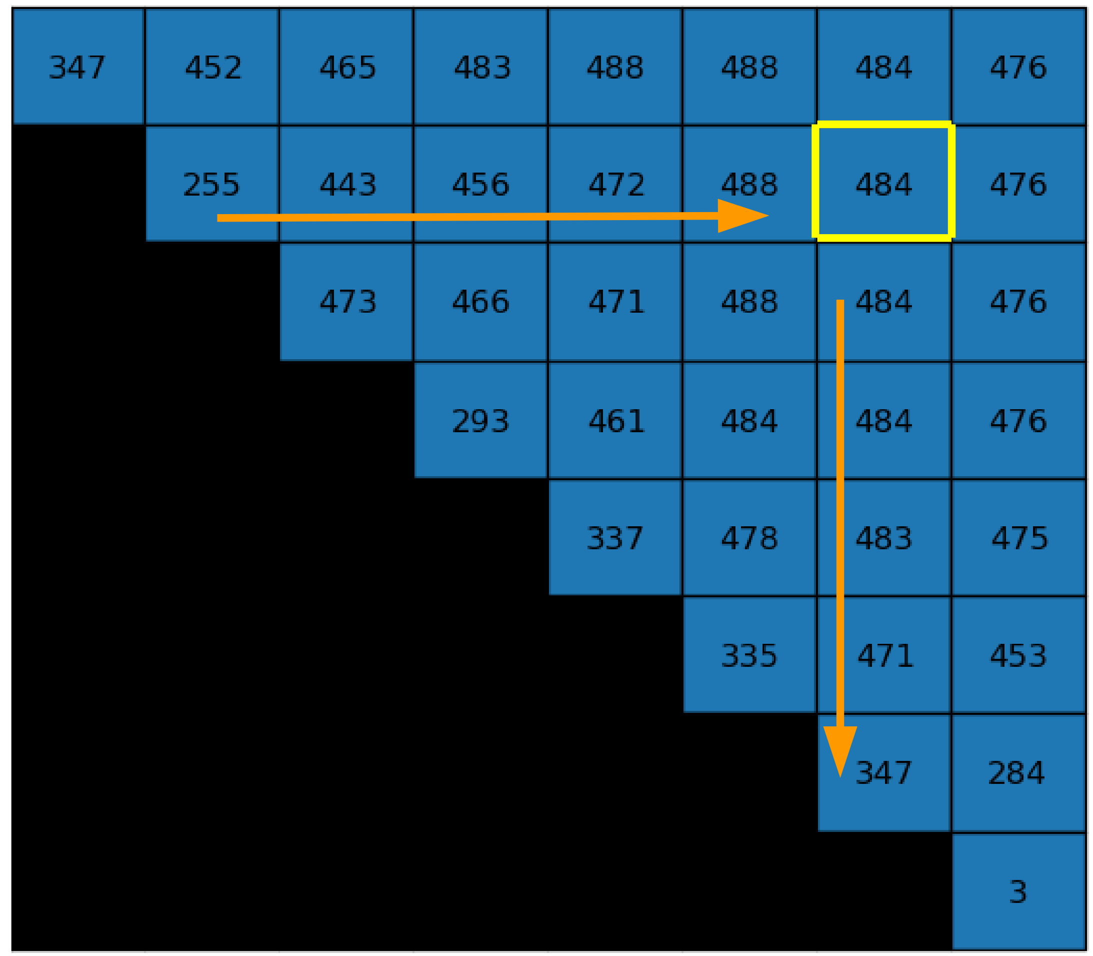
Runtime?

$O(G^*n^3)$

O(n^2) cells
O(G*n) time to fill each

How many grammar lookups to fill this cell

#symbols in each cell of a realistic grammar



255*484
+ 443*484
+ 456*483
+ 472*471
+ 488*347
= **949,728**

Almost a million lookups for one cell!

Runtime with Jacobian

$$\text{runtime}(\pi + \varepsilon \mathbf{1}_j) = \sum_x \mathbf{1}\left[\beta_x(\pi) + \varepsilon \cdot \frac{\partial \beta_x(\pi)}{\partial \pi_j} > 0\right]$$

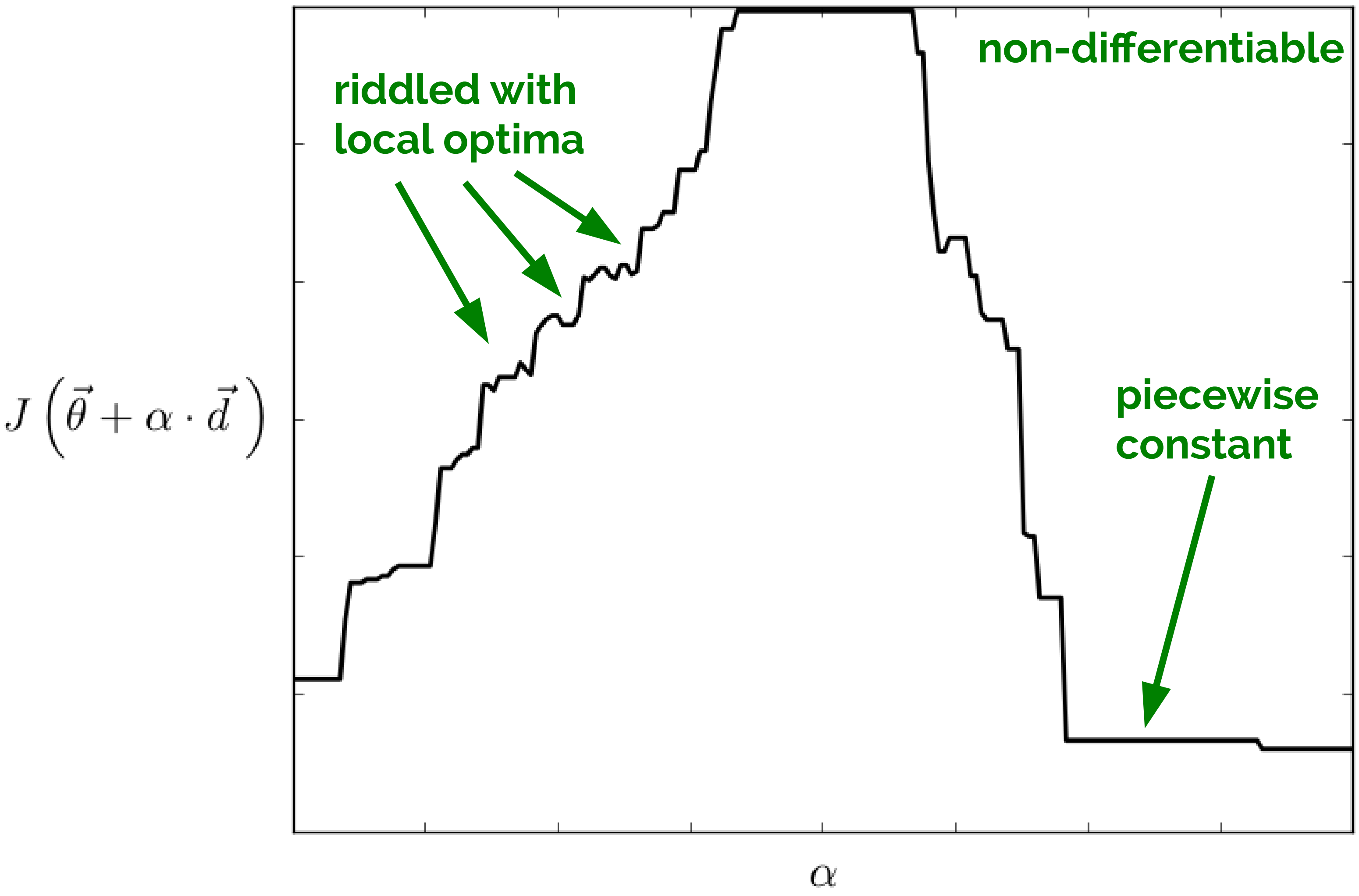
General trick: apply expansion before nonlinearity.

Needs T Jacobian-vector products → asymptotically slower than running inference T times.

Just want Booleans in the end → changeprop will be faster.

Tricky to optimize

Cross-section of objective, J, along a random direction, d

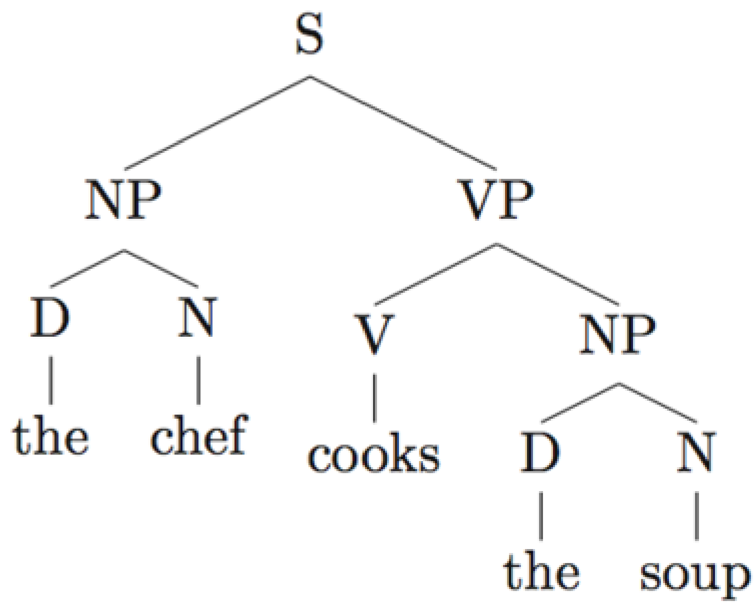


Pruning is a discrete decision

Parsing

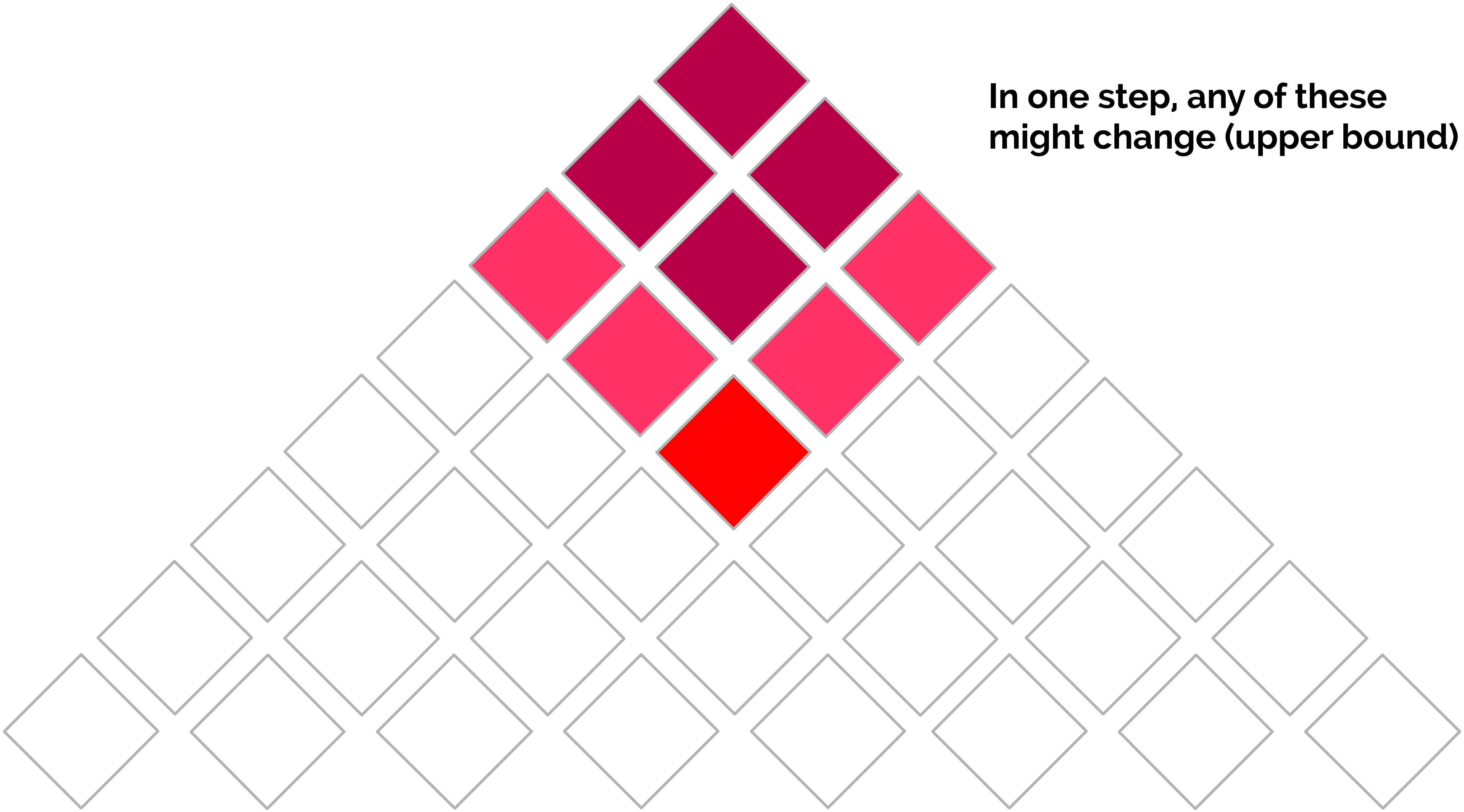
"diagramming sentences"

Parse



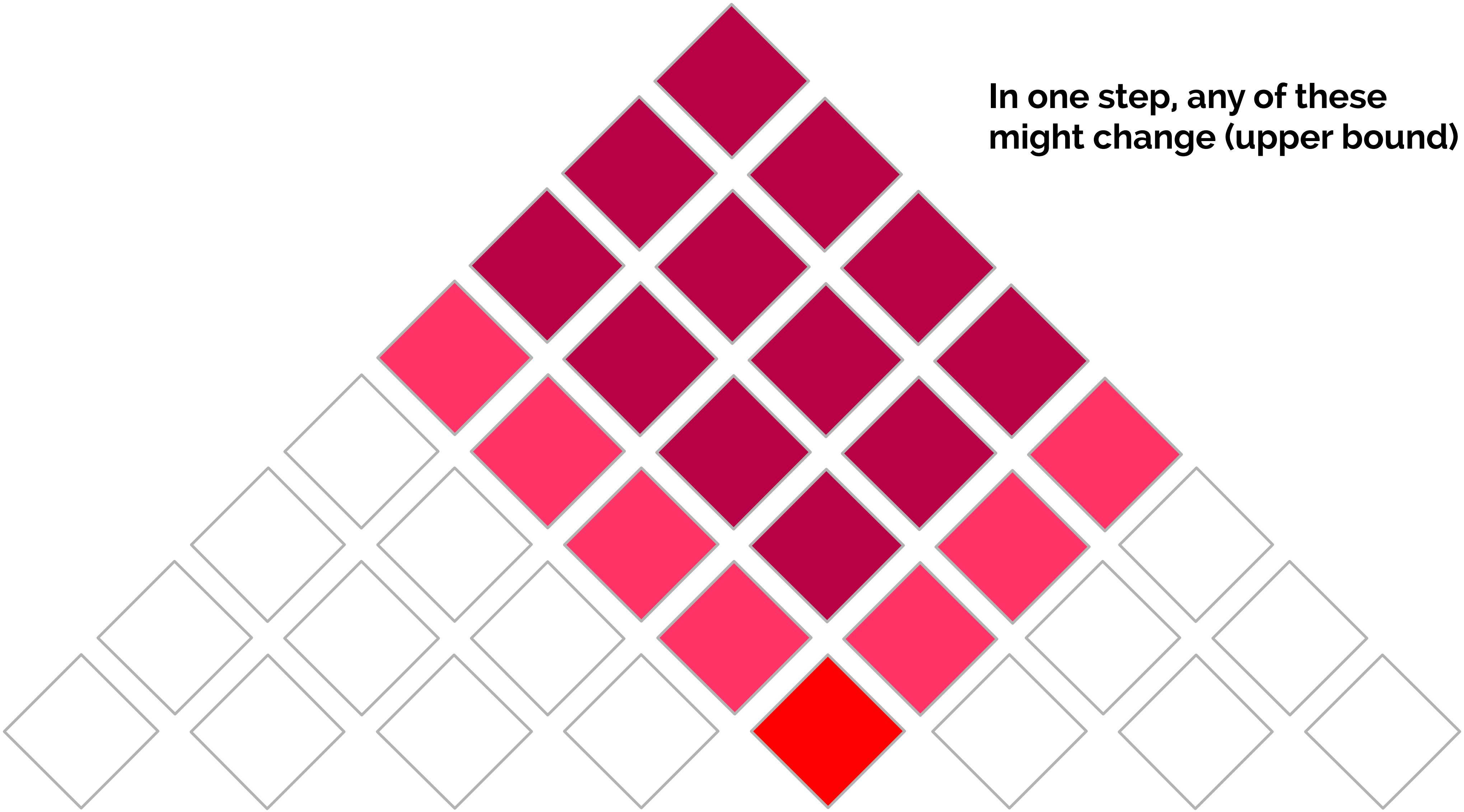
Sentence

Changeprop



In one step, any of these might change (upper bound)

Changeprop



In one step, any of these might change (upper bound)

Dynamic program (cheat sheet)

Suppose final reward is expected reward instead of one-best

$$r = \bar{r} / Z \qquad Z = \sum_d \prod_{e \in d} k_e$$

(1) To start: what if we change just one edge?

$$\bar{r} = \sum_d r(d) p(d) = \sum_d r(d) \prod_{e \in d} k_e$$

(2) Multi-linear functions of single edge weights

(3) Multi-linear (example): **f(x,y,z) = xyz** not jointly linear, but is linear in x, y or z, separately (i.e., hold others fixed).

(4) No edge appears twice in a given derivation. Note: r(d) can't depend on edge weights.

(5) Compute change with Taylor expansion:

$$\bar{r}(\vec{k} + \varepsilon \cdot \vec{1}_e) = \bar{r}(\vec{k}) + \varepsilon \cdot \frac{\partial \bar{r}}{\partial k_e}$$

Similarly for Z.

Similar trick for runtime requires Jacobian. Not very efficient

(7) Take quotient

(8) Need additive reward to efficiently compute. Use second-order inside-outside or backprop to get gradients.

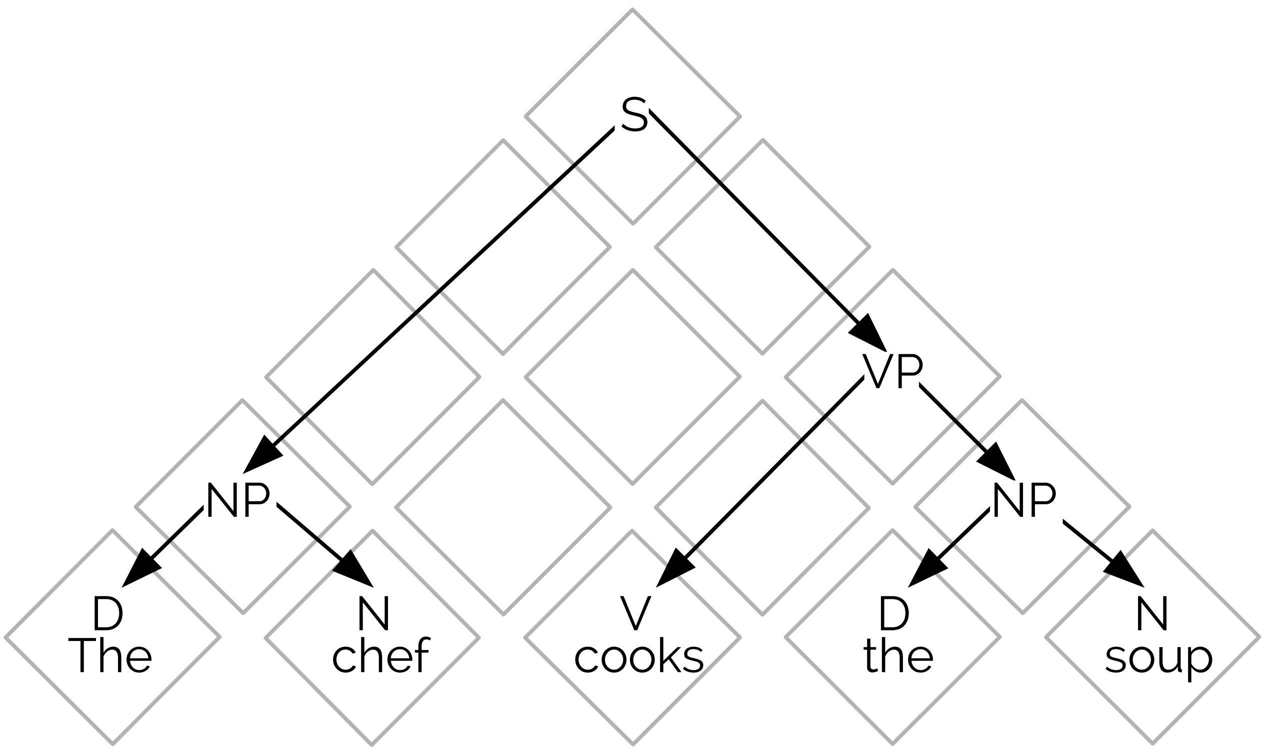
→ All T=O(n^2) rollouts for the cost of one!

Tweaks:

(9) Pruning changes multiple edges.

(10) Use annealing to recover one-best

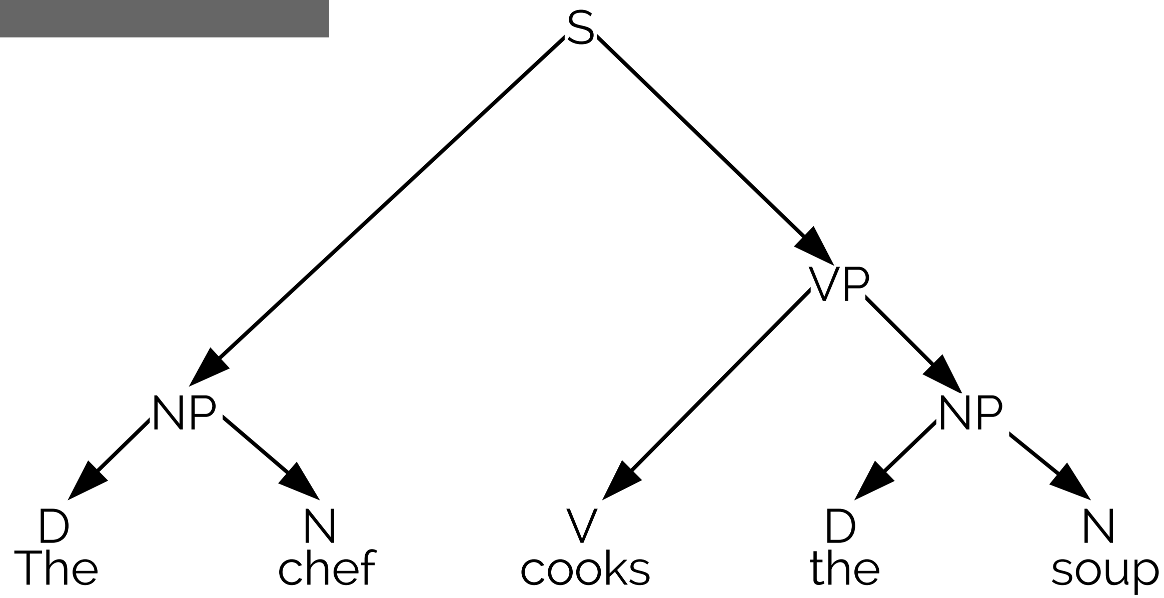
Parsing



Parsing

"Diagramming sentences"

Intuition: the substitution test



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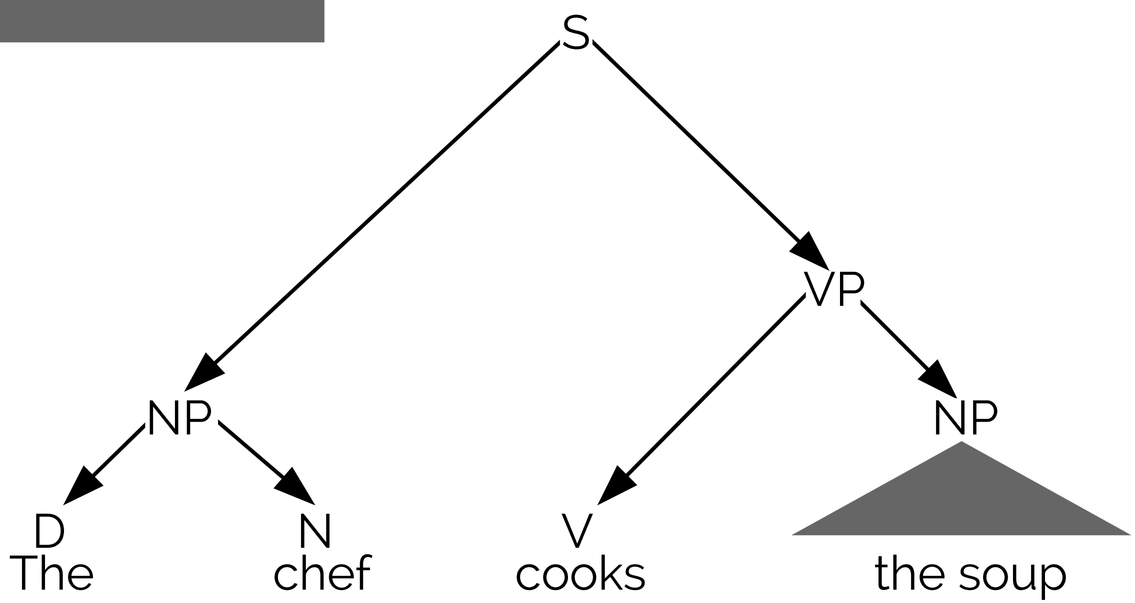

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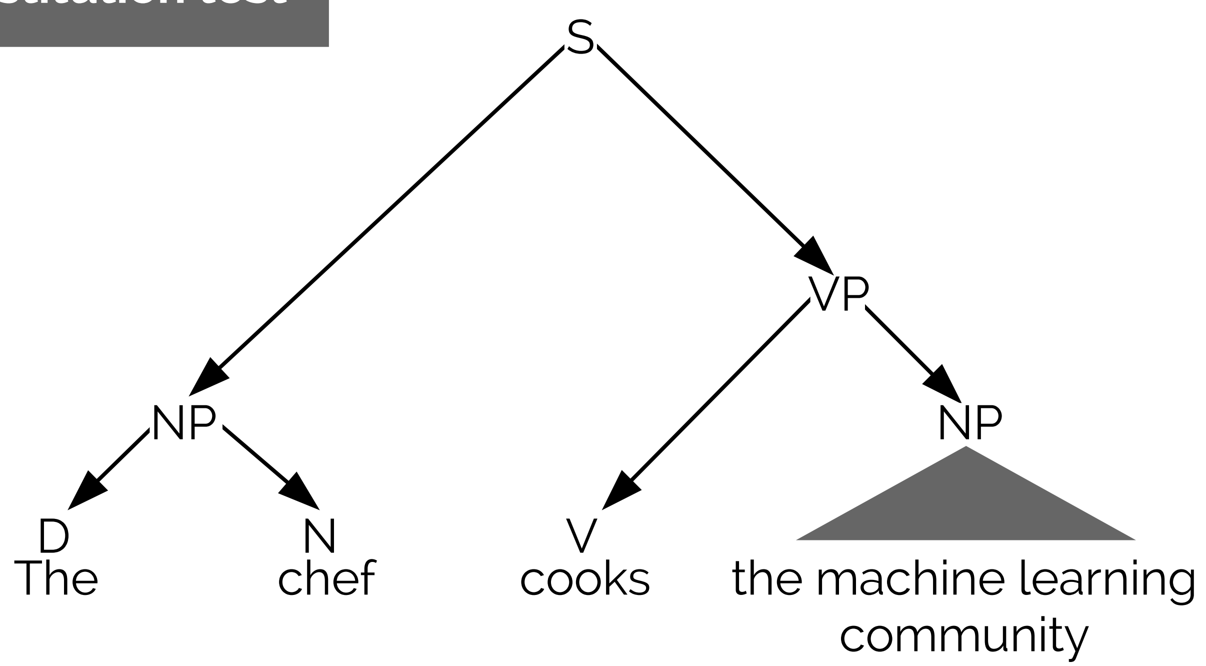

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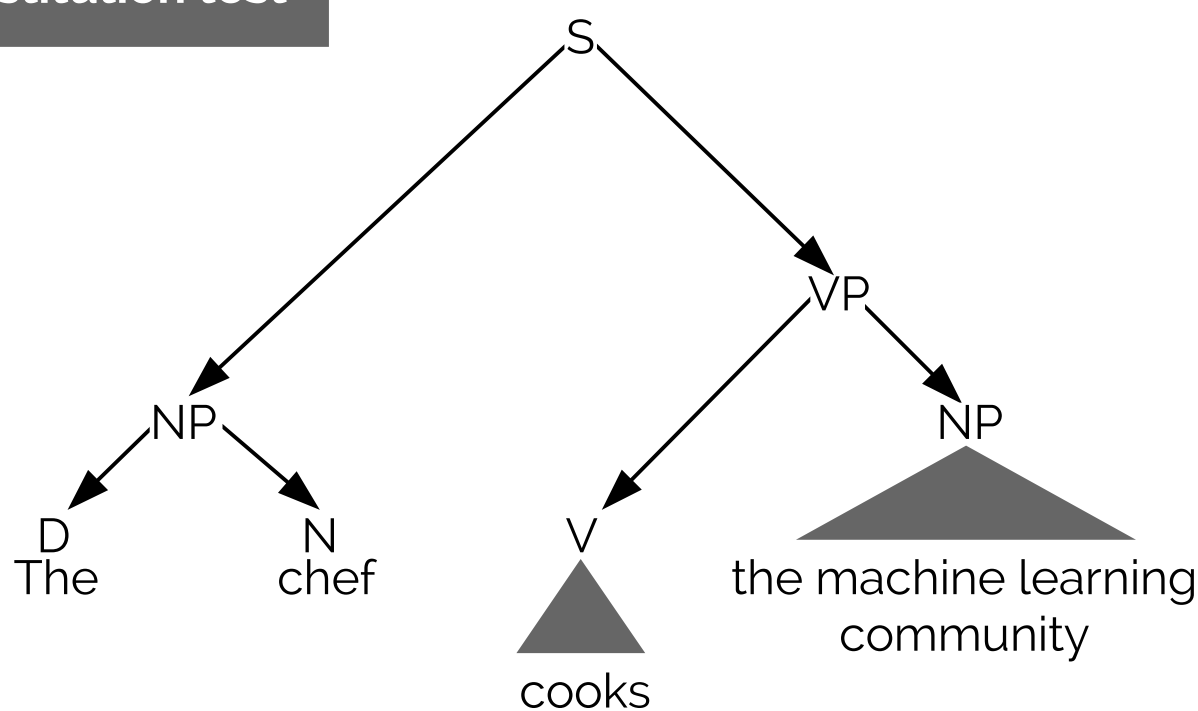

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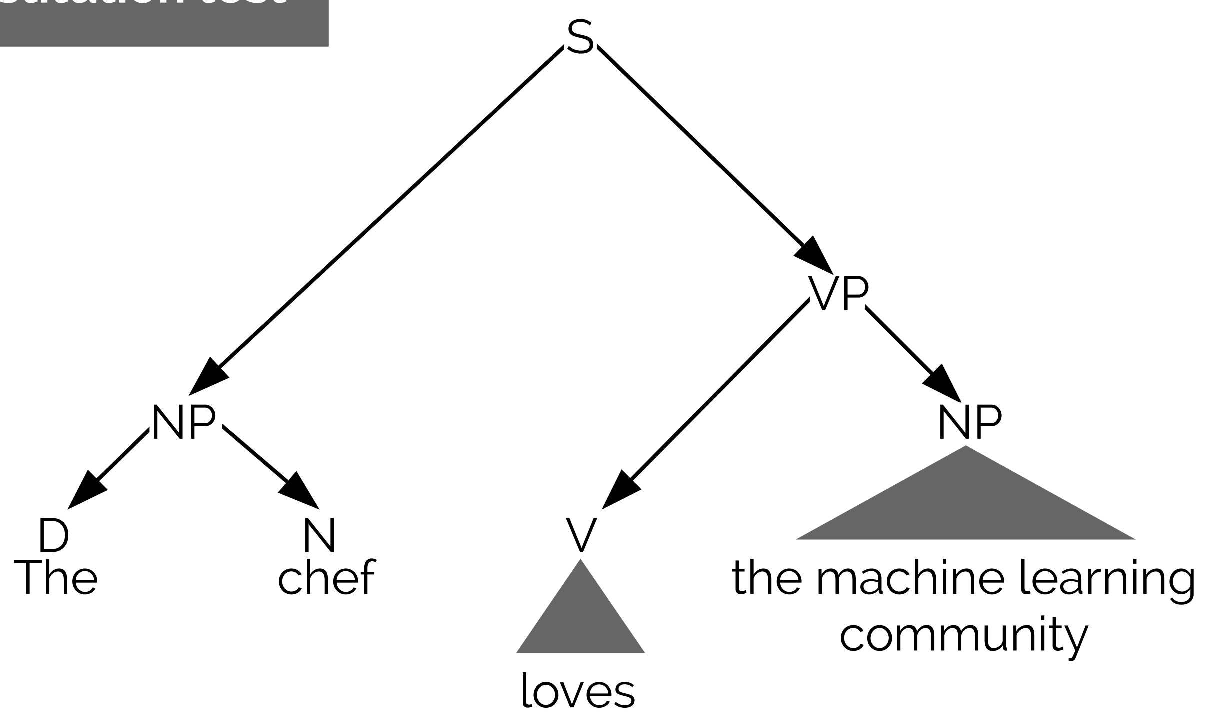

Parsing

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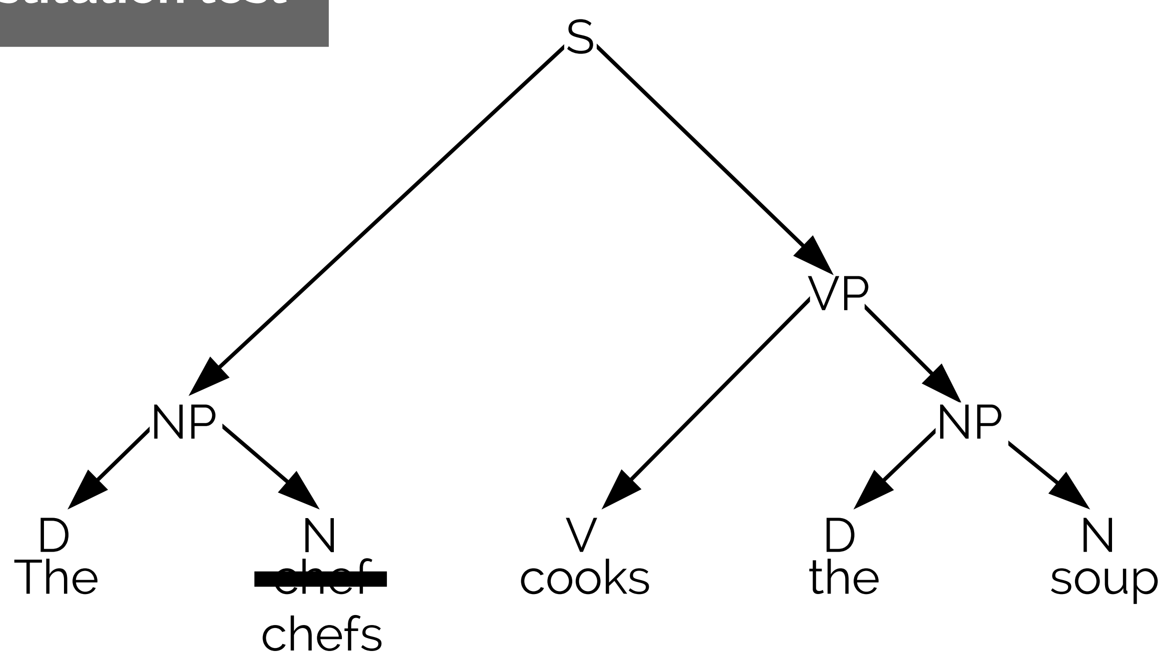
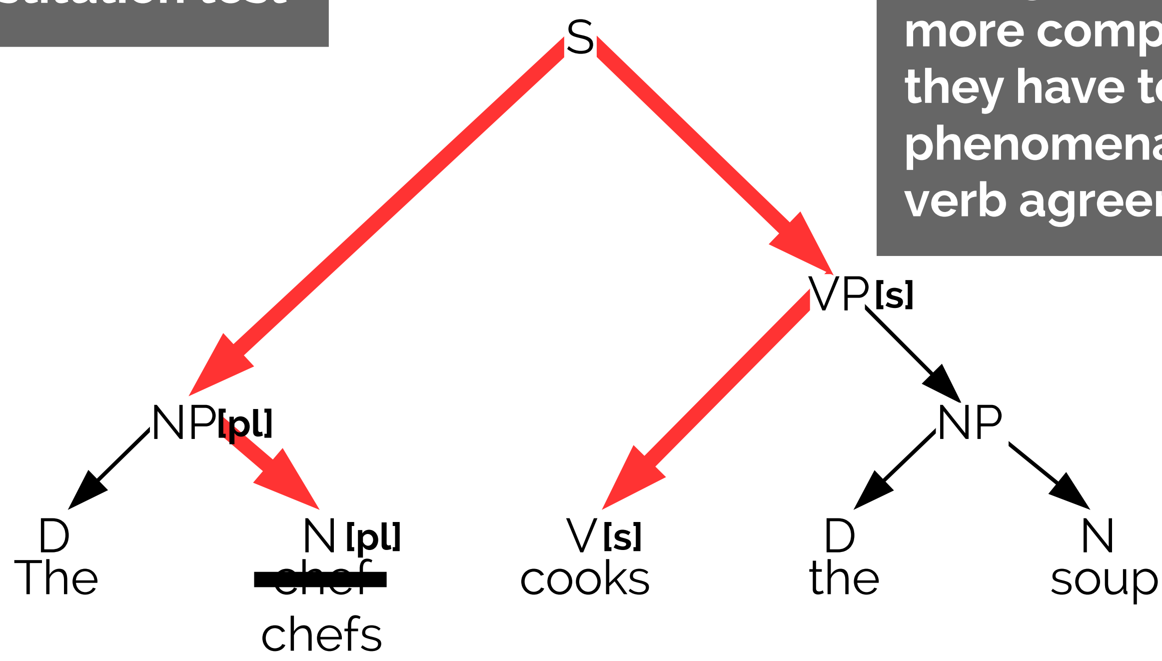


Parsing

What is a good derivation for this sentence?

Intuition: the substitution test



Real grammars are much more complex because they have to capture lots of phenomena (e.g., subject-verb agreement)