Synthetic Data Made to Order: The Case of Parsing

Dingquan Wang and Jason Eisner
Department of Computer Science
Johns Hopkins University

Acknowledgement

JOHNS HOPKINS
UNIVERSITY

Acknowledgement

- Universal Dependencies

Acknowledgement

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  - Now has **122** treebanks, **71** languages

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  - Empower the supervised methods to process these languages

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  - Help analyze novel languages

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Transfer Parsing

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French Corpus

Ma mère s'appelle Emilie Summer

Lundi, je retourne à l'école

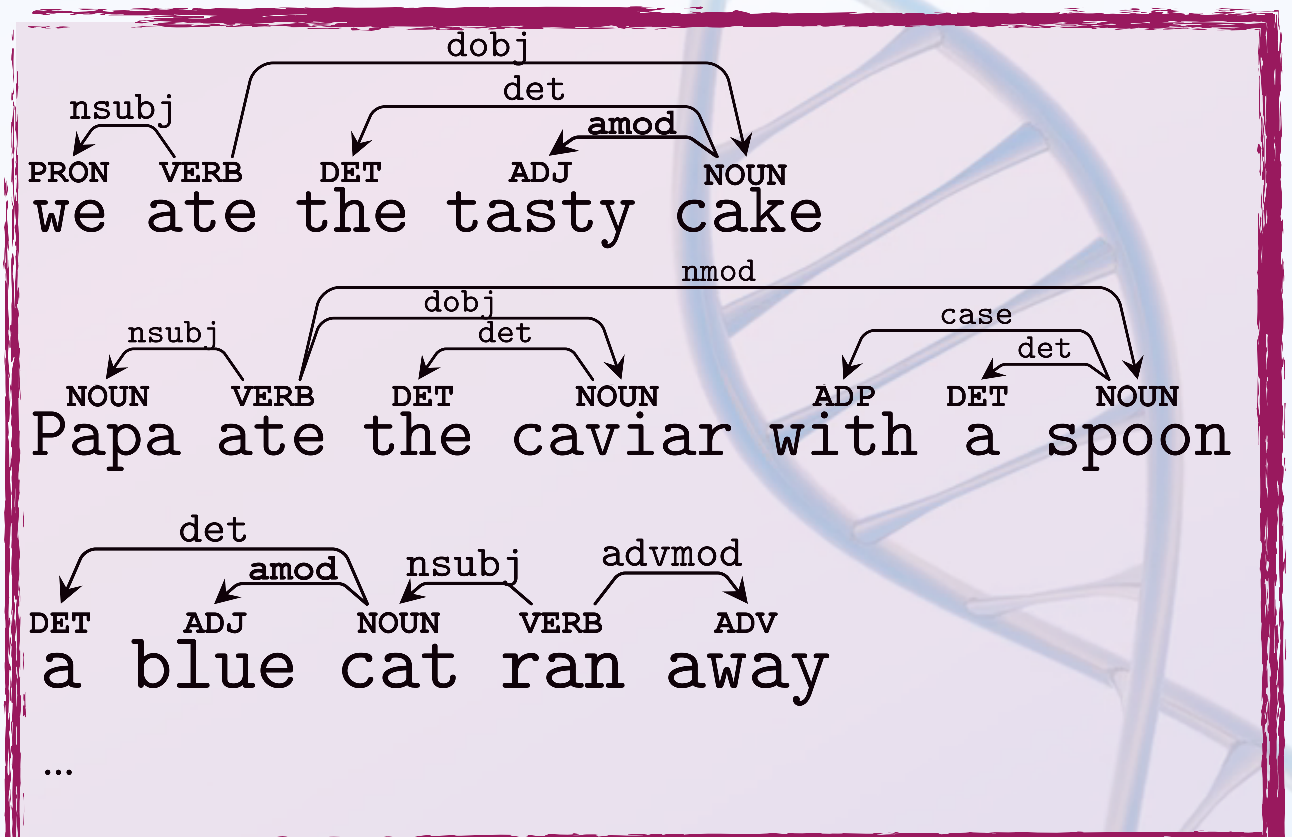
C'est ma meilleure amie

J'aime beaucoup l'école

…

Transfer Parsing

English Treebank



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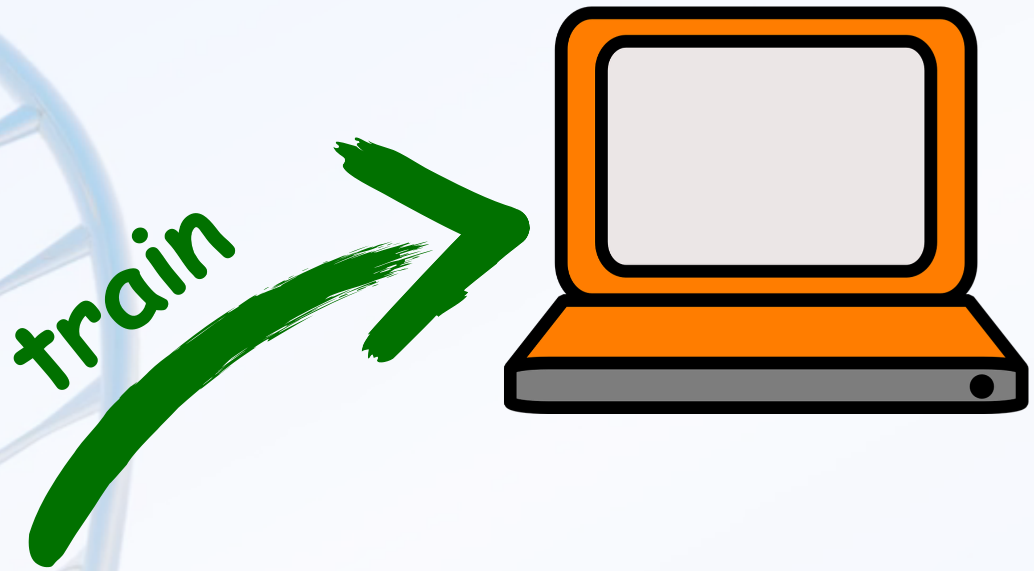
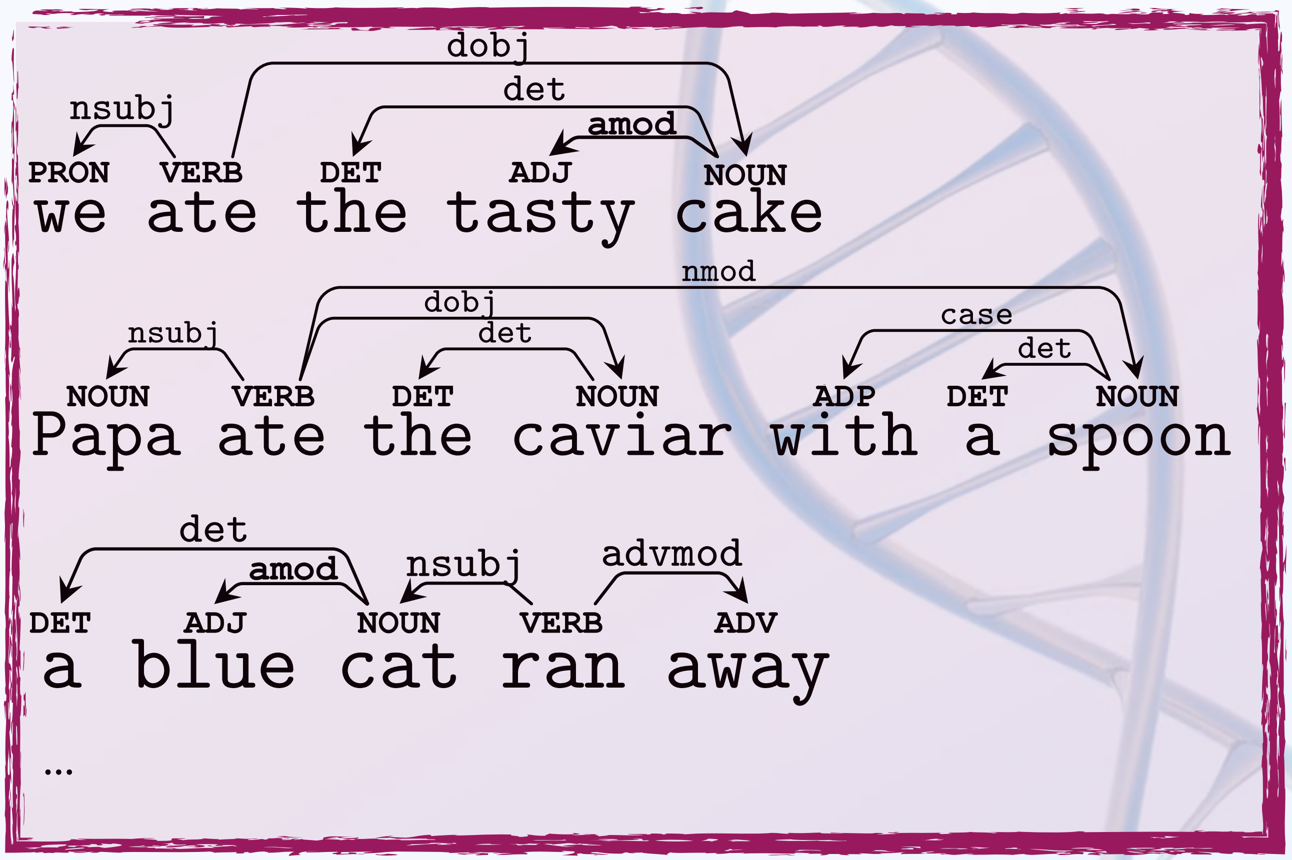


English Treebank



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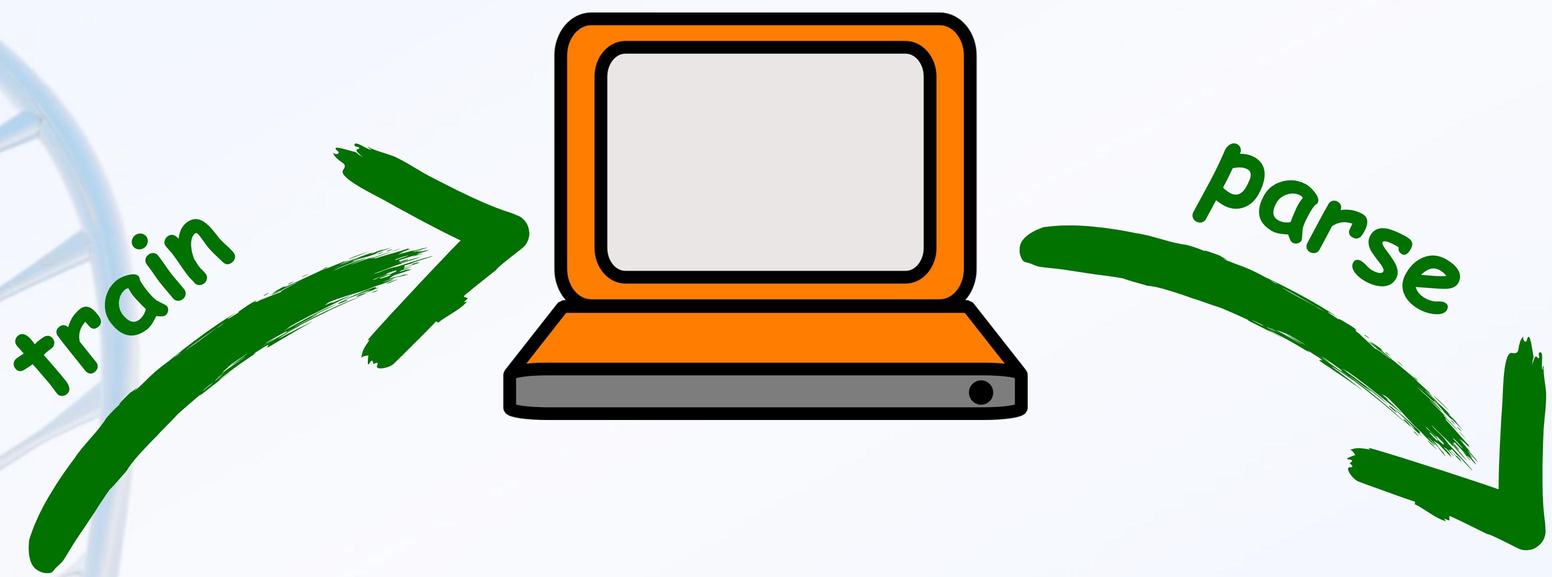
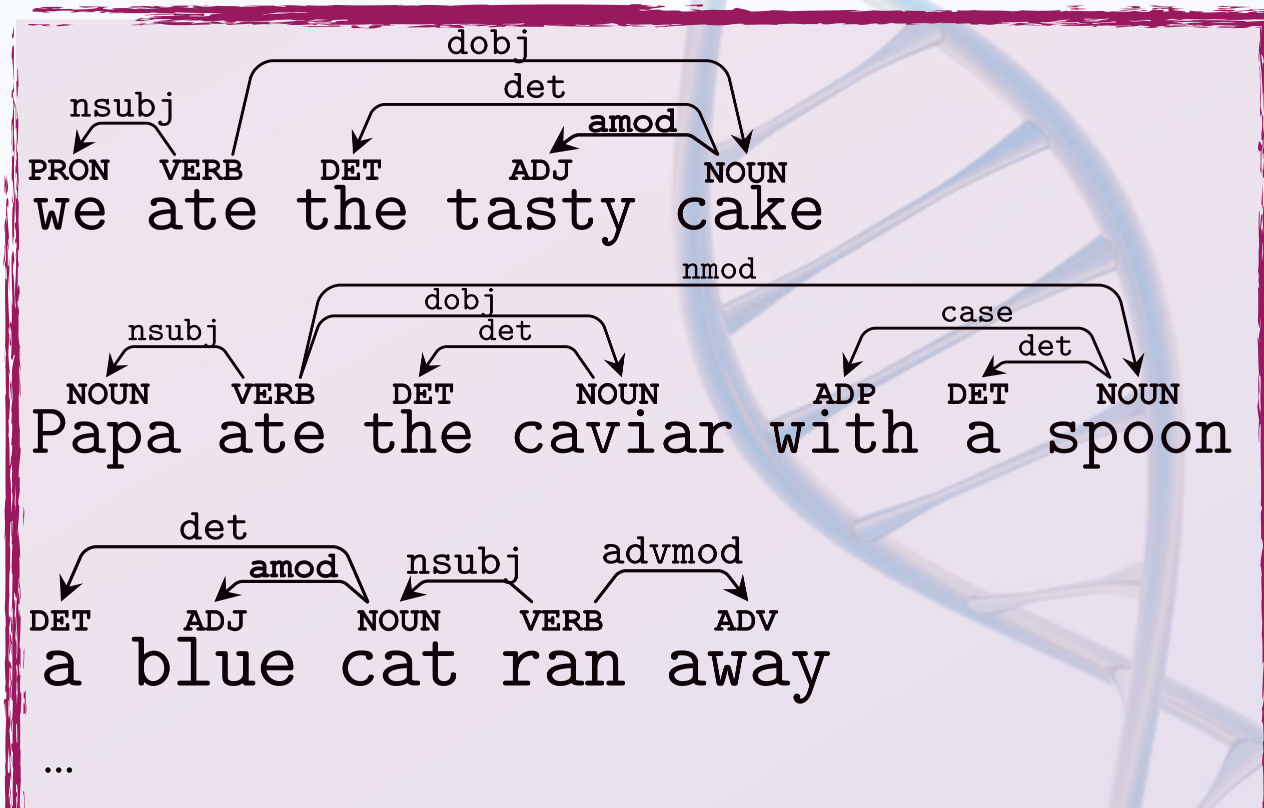


English Treebank



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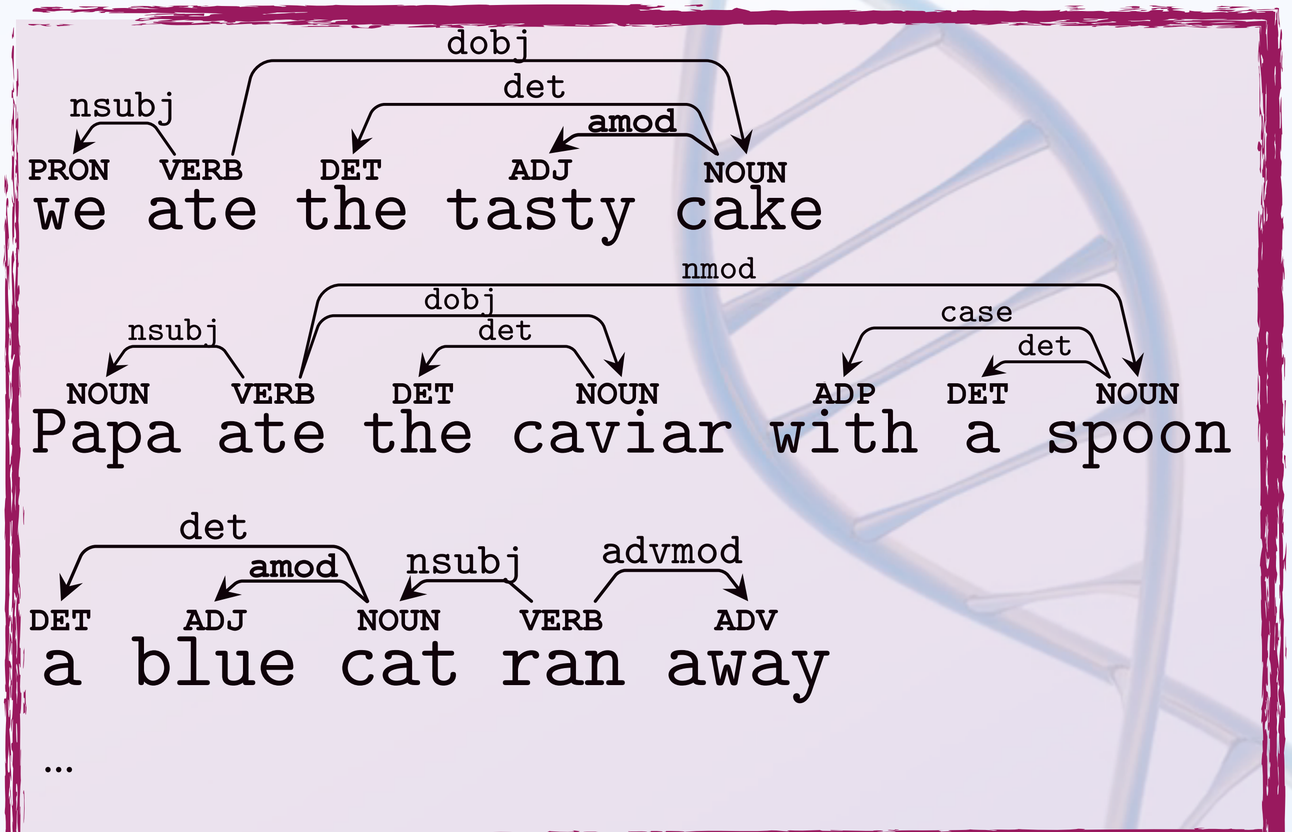

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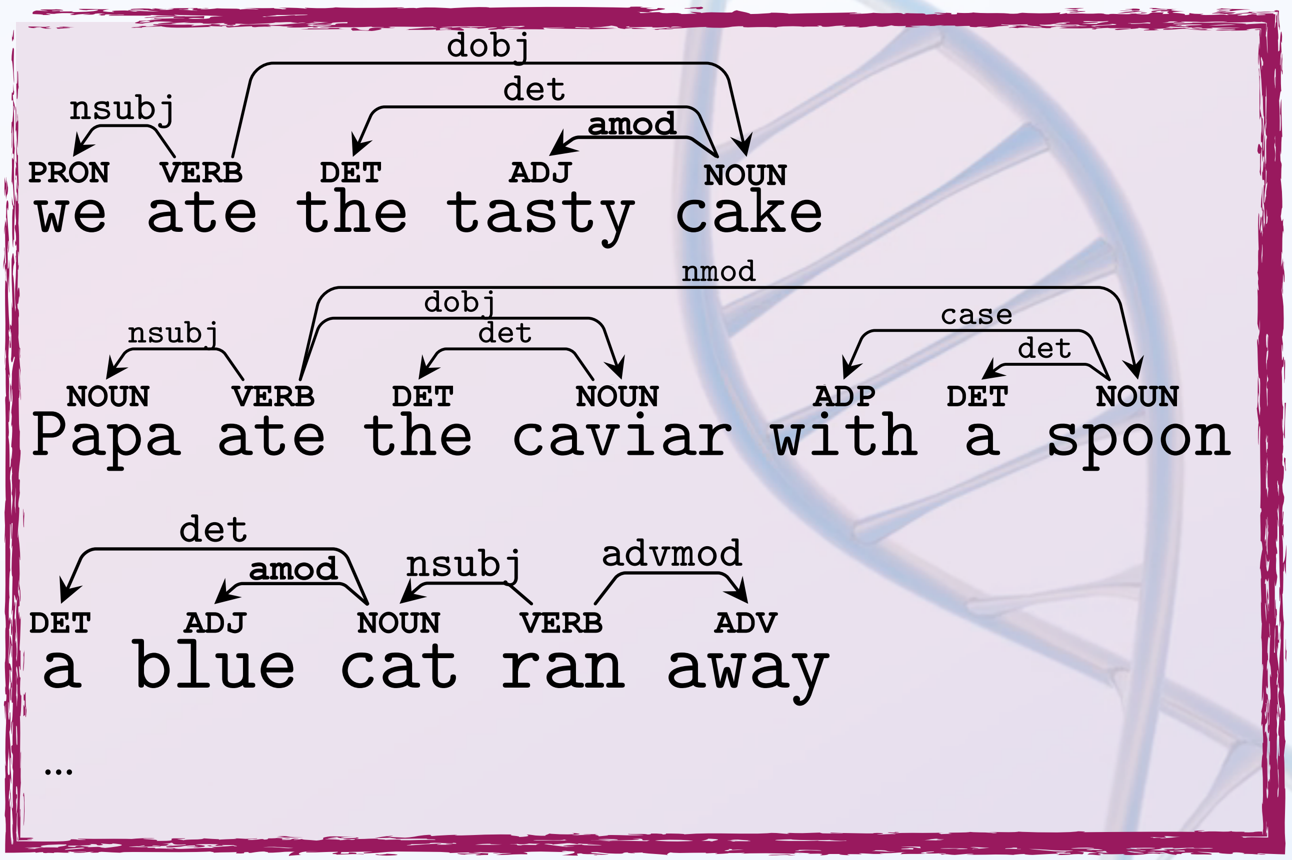

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Delexicalized Transfer Parsing

English Delex Treebank

```
              dobj
 nsubj          det
                     amod
PRON  VERB  DET    ADJ    NOUN

                       nmod
              dobj
 nsubj          det               case
                                     det
NOUN  VERB  DET    NOUN      ADP  DET  NOUN

      det                nsubj
         amod                       advmod
DET   ADJ   NOUN              VERB    ADV

...
```

French POS Corpus

NOUN VERB DET NOUN ADJ ADP NOUN

NOUN VERB PART NOUN

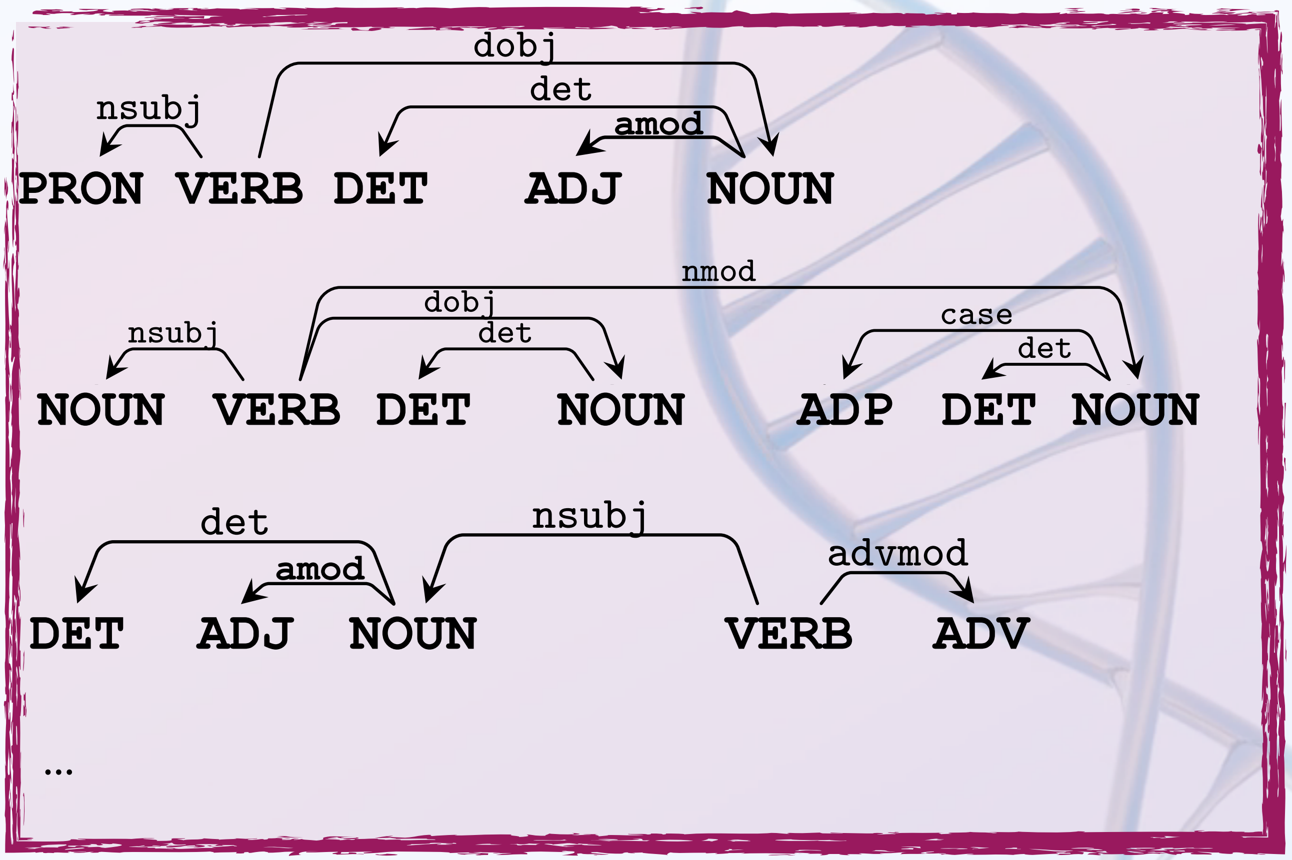
DET NOUN ADJ VERB

PRON VERB ADP DET NOUN

...

Delexicalized Transfer Parsing

English Delex Treebank



French POS Corpus

NOUN VERB DET **NOUN ADJ** ADP NOUN

NOUN VERB PART NOUN

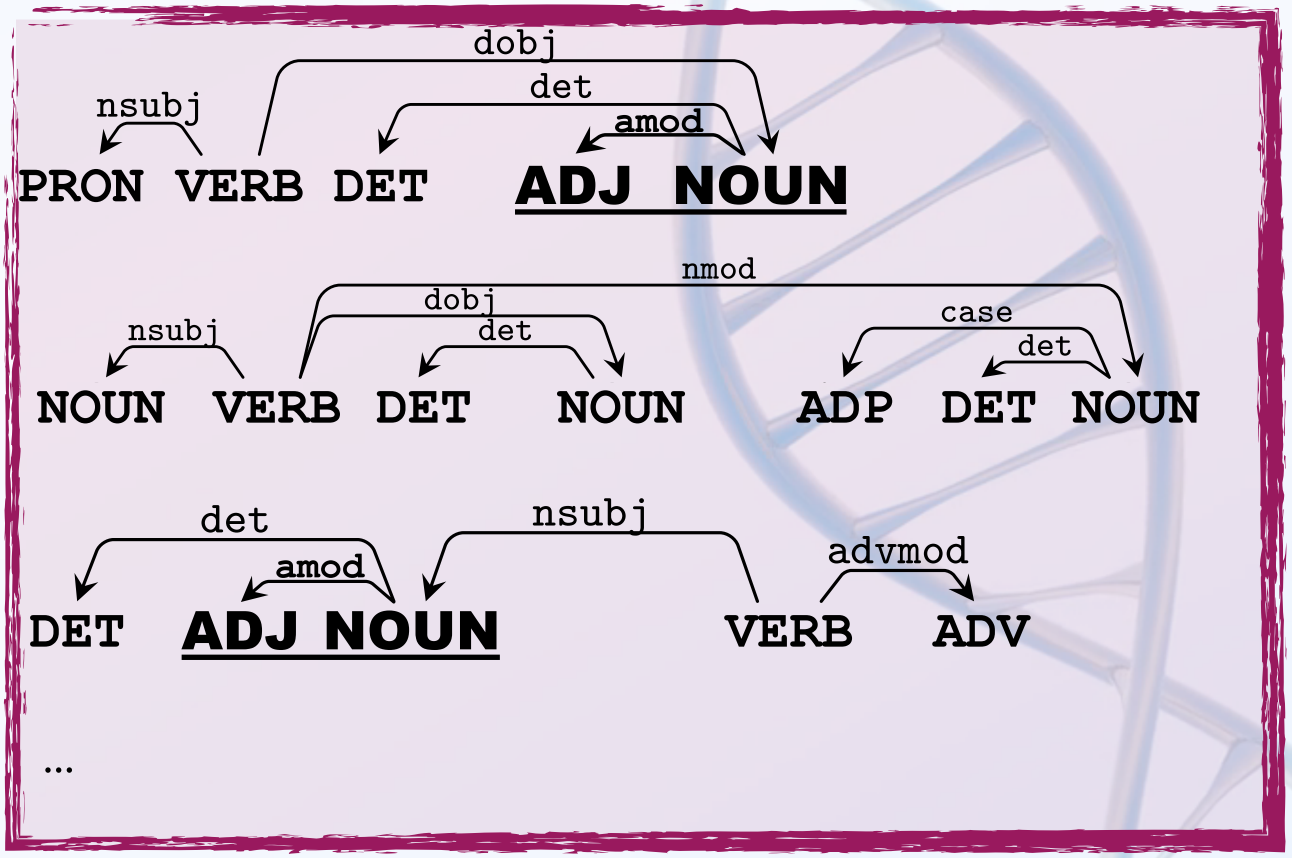
DET **NOUN ADJ** VERB

PRON VERB ADP DET NOUN

…

Delexicalized Transfer Parsing

English Delex Treebank



French POS Corpus

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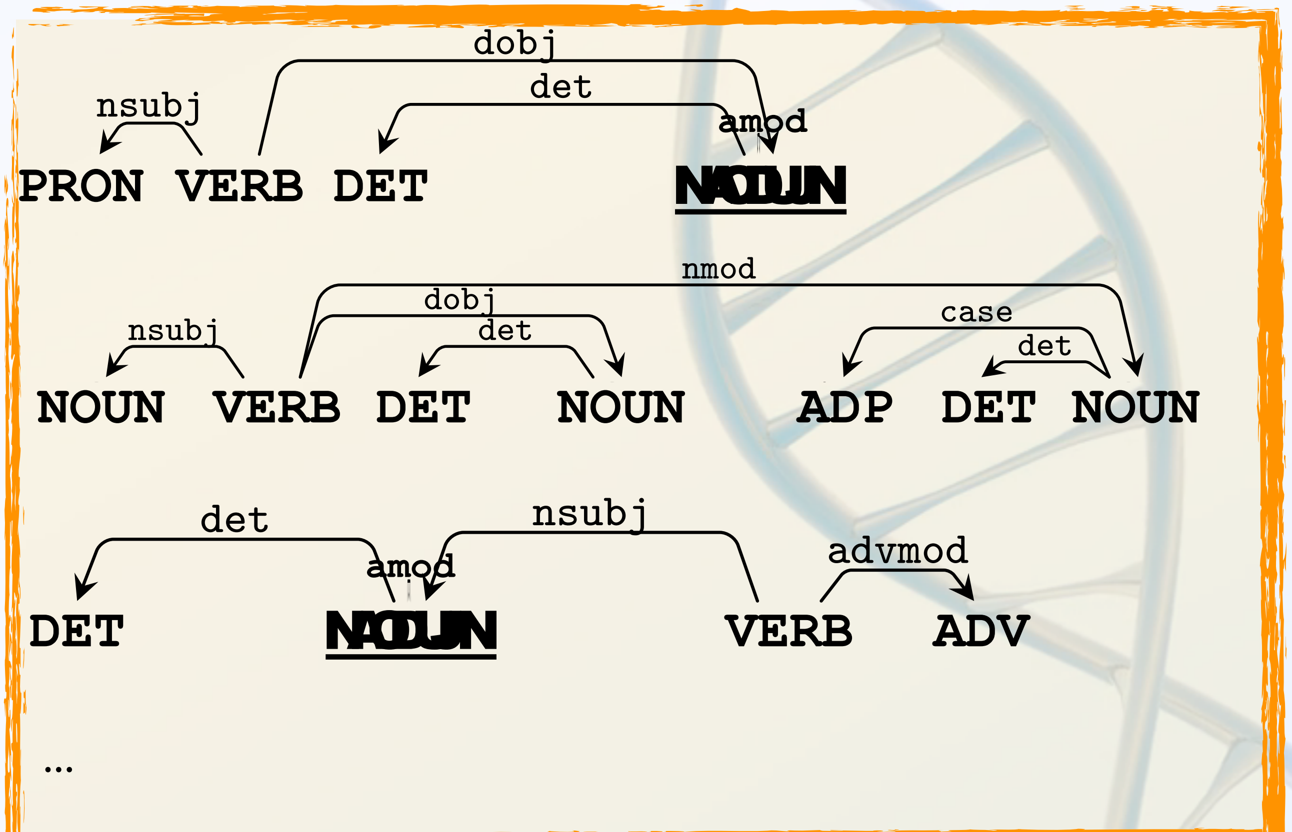
Delexicalized Transfer Parsing

English Delex Treebank



French POS Corpus

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NOUN VERB PART NOUN

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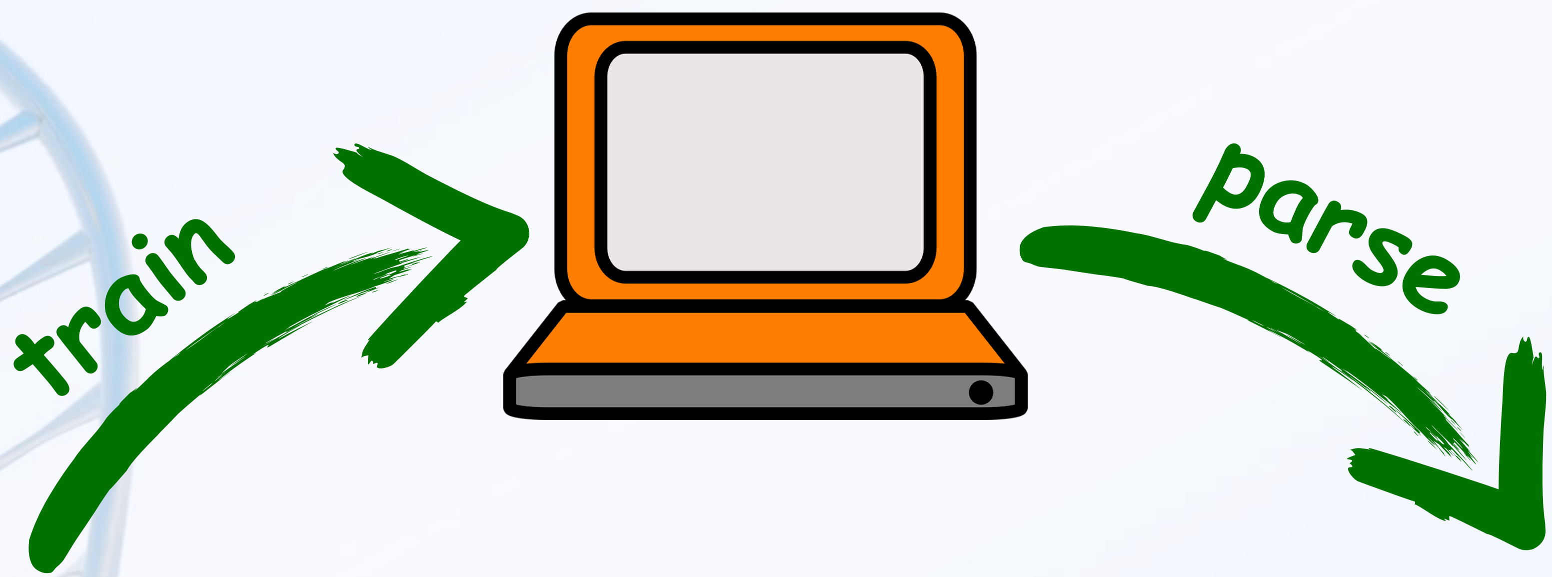
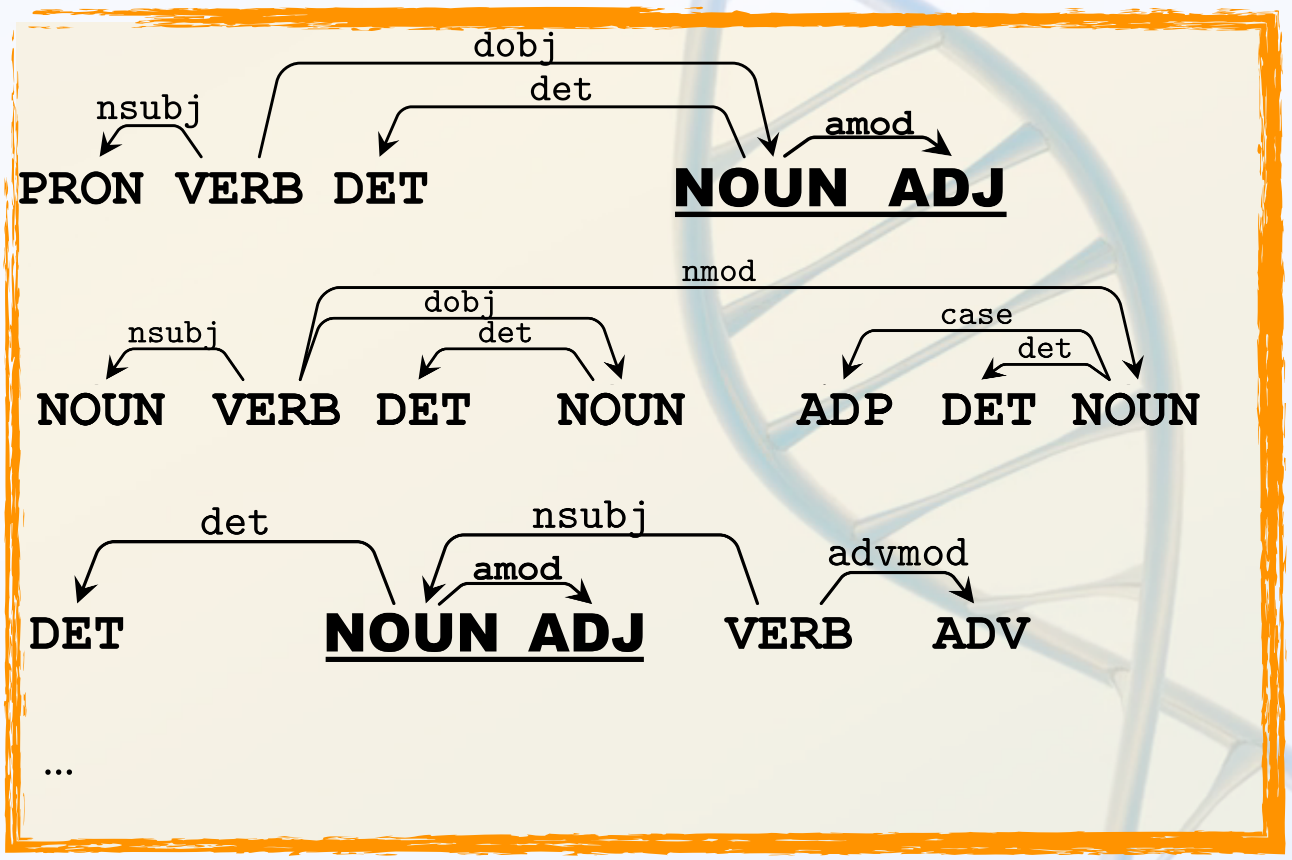
Delexicalized Transfer Parsing



English' Delex Treebank



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DET **NOUN ADJ** VERB

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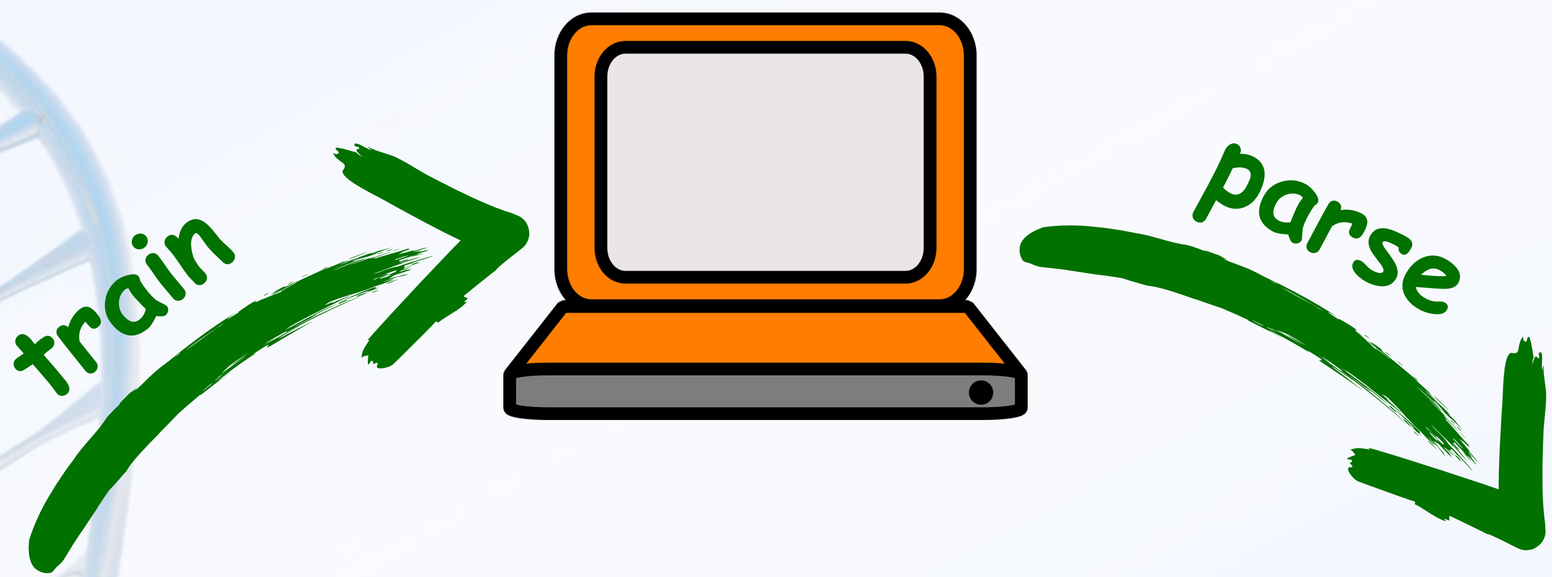
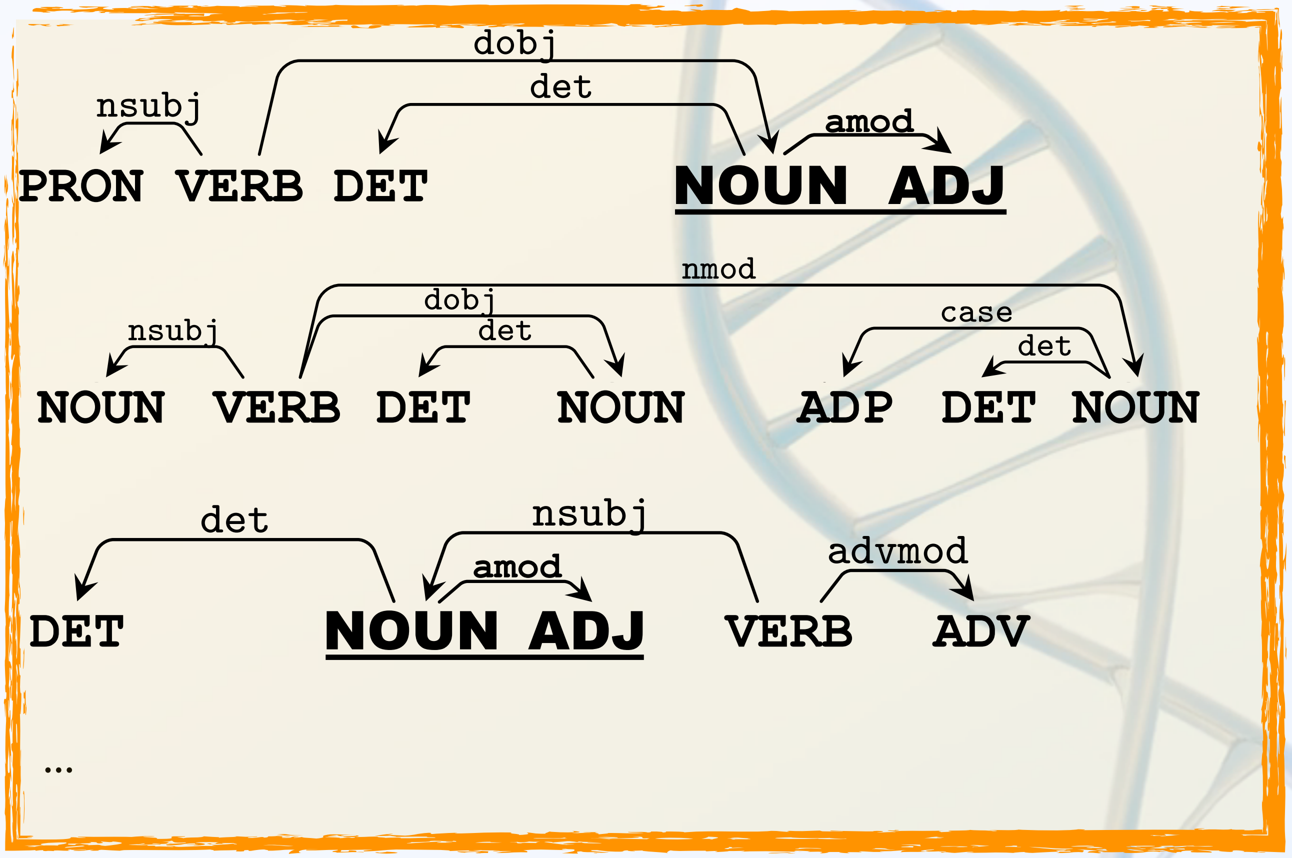
Delexicalized Transfer Parsing



English' Delex Treebank



French POS Corpus

NOUN VERB DET **NOUN ADJ** ADP NOUN

NOUN VERB PART NOUN

DET **NOUN ADJ** VERB

PRON VERB ADP DET NOUN

…

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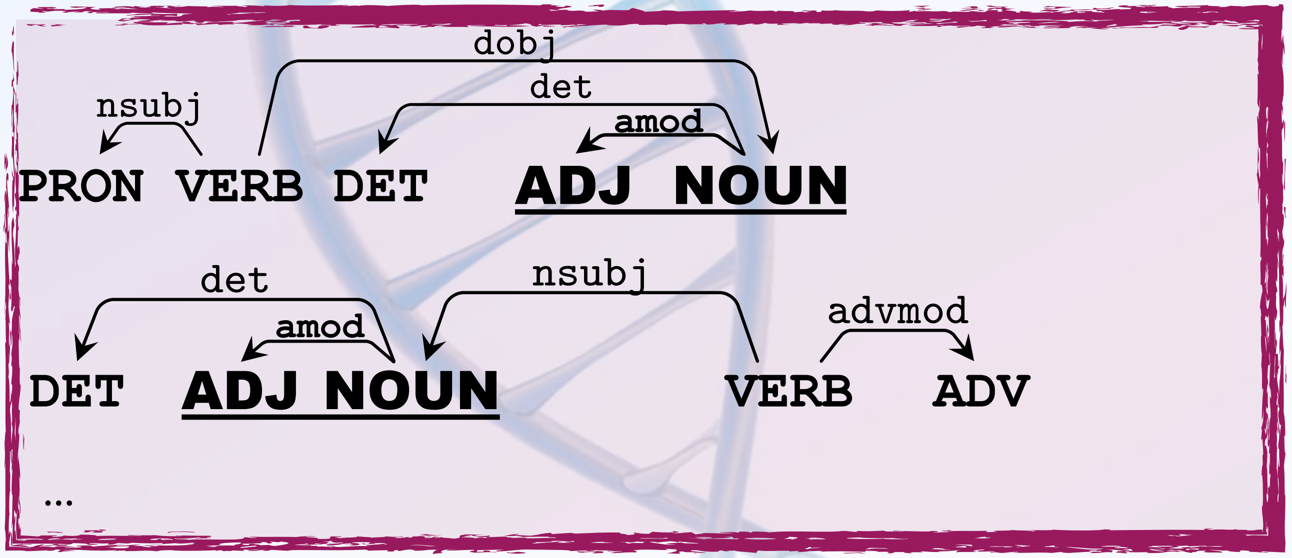
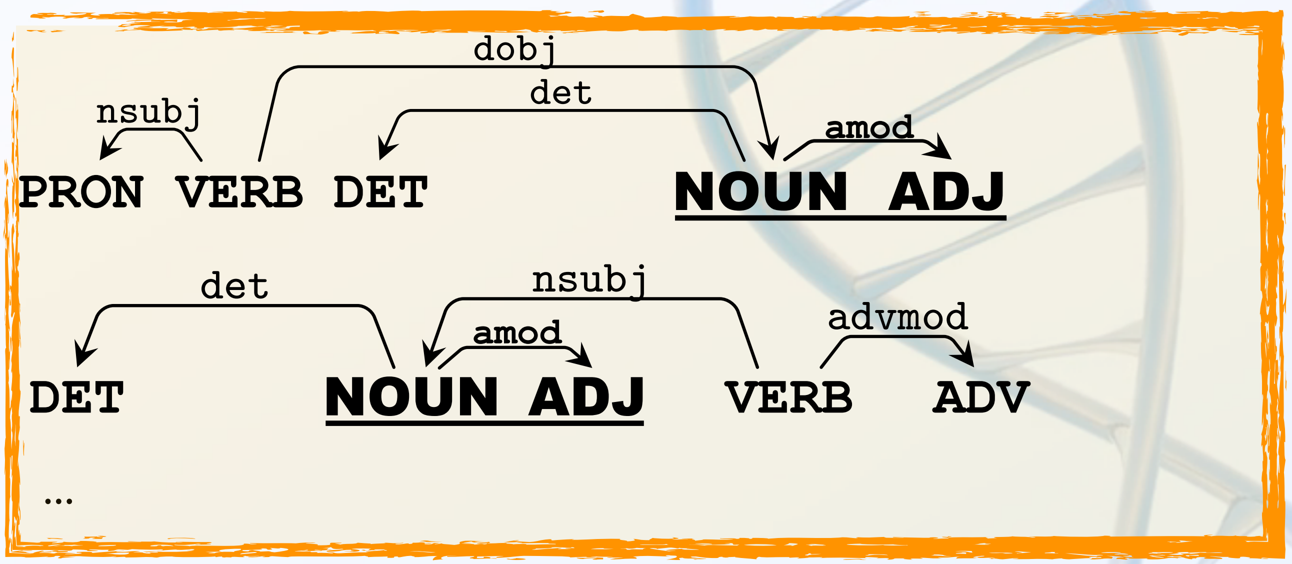
Improve the surface similarity

English



English'



French POS Corpus

NOUN VERB DET **NOUN ADJ** ADP NOUN

NOUN VERB PART NOUN

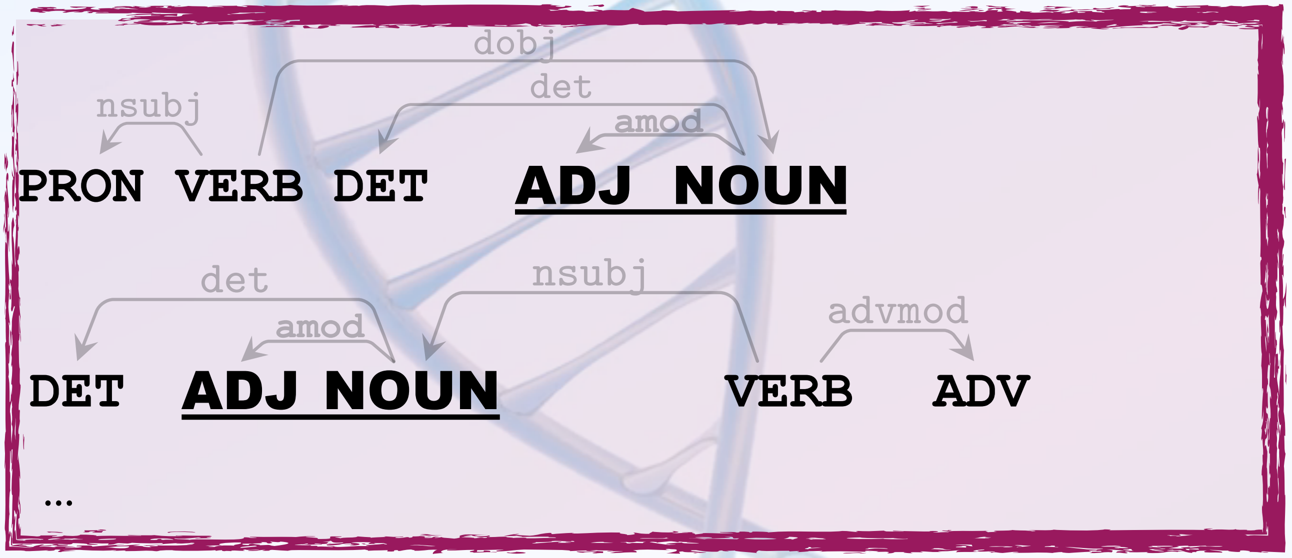
DET **NOUN ADJ** VERB

PRON VERB ADP DET NOUN

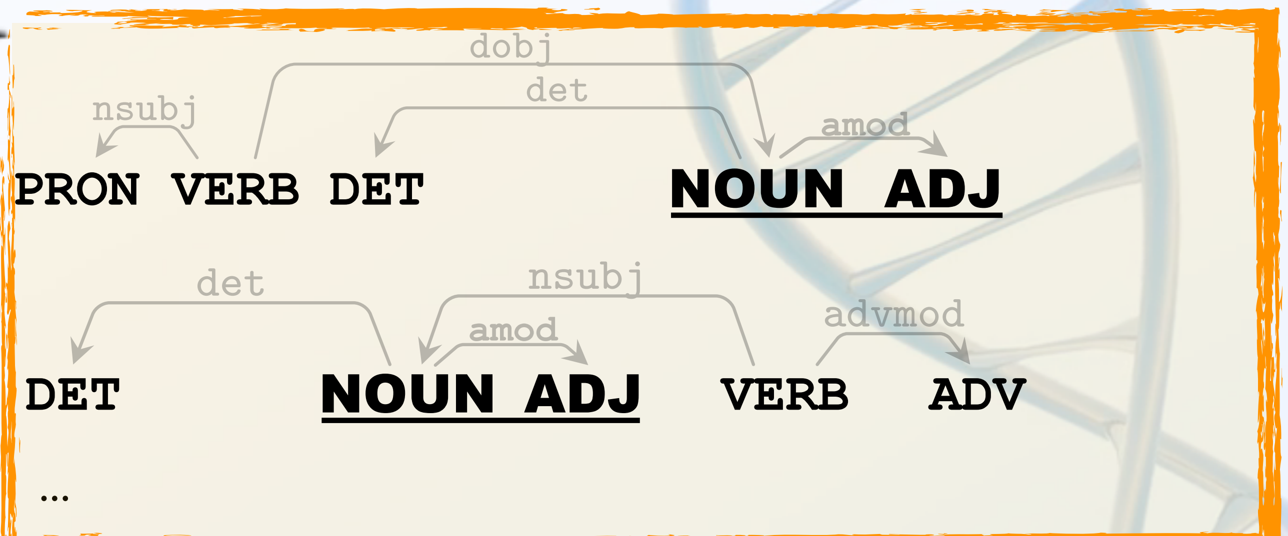
…

Improve the surface similarity

English



English'



French POS Corpus

NOUN VERB DET **NOUN ADJ** ADP NOUN

NOUN VERB PART NOUN

DET **NOUN ADJ** VERB

PRON VERB ADP DET NOUN

…

Improve the surface similarity

English

dobj det nsubj amod

PRON VERB DET **ADJ NOUN**

det nsubj amod advmod

DET **ADJ NOUN** VERB ADV

…

English'

dobj det nsubj amod

PRON VERB DET **NOUN ADJ**

det nsubj amod advmod

DET **NOUN ADJ** VERB ADV

…

French POS Corpus

NOUN VERB DET **NOUN ADJ** A… NOUN

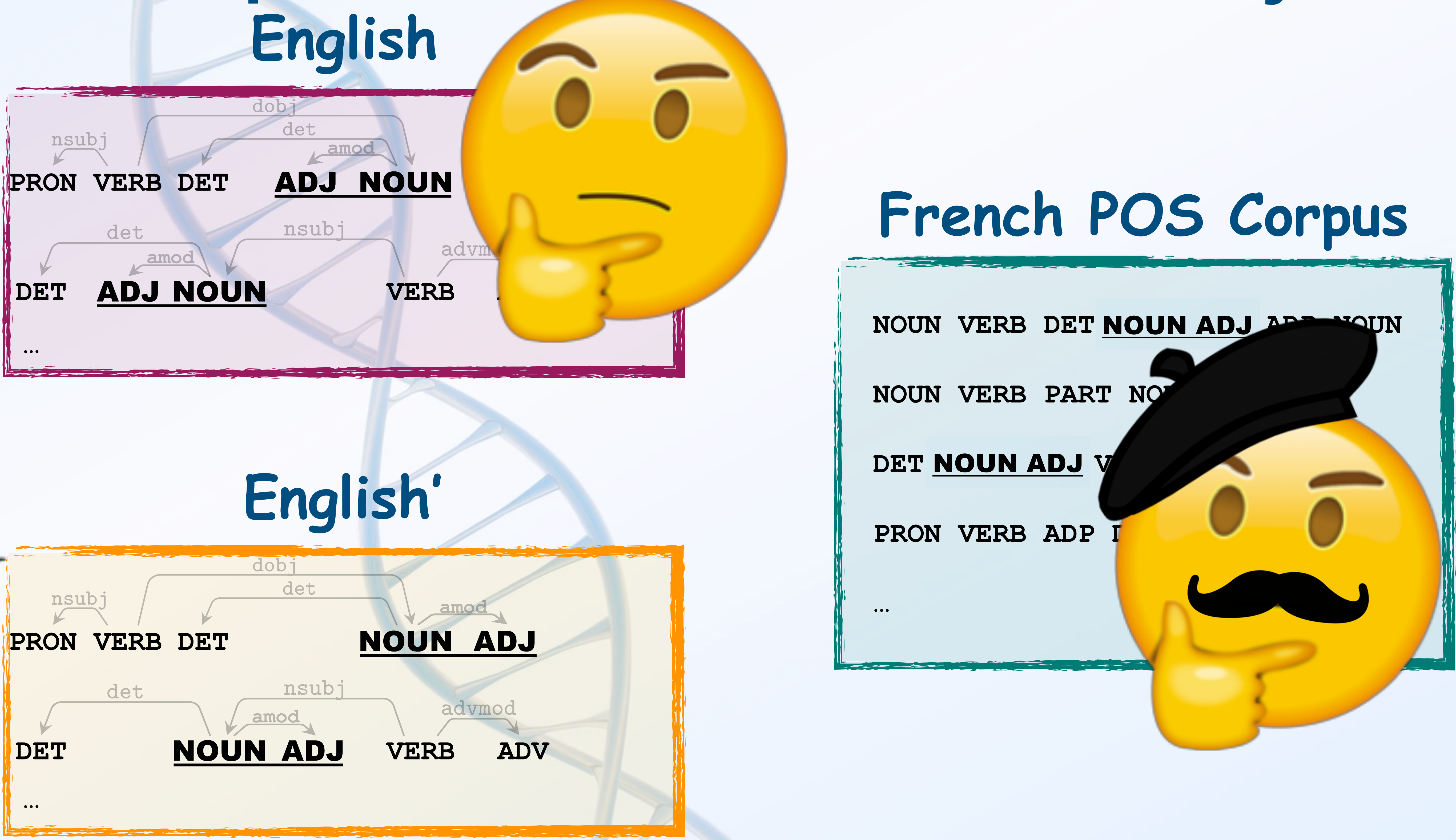
NOUN VERB PART NO…

DET **NOUN ADJ** V…

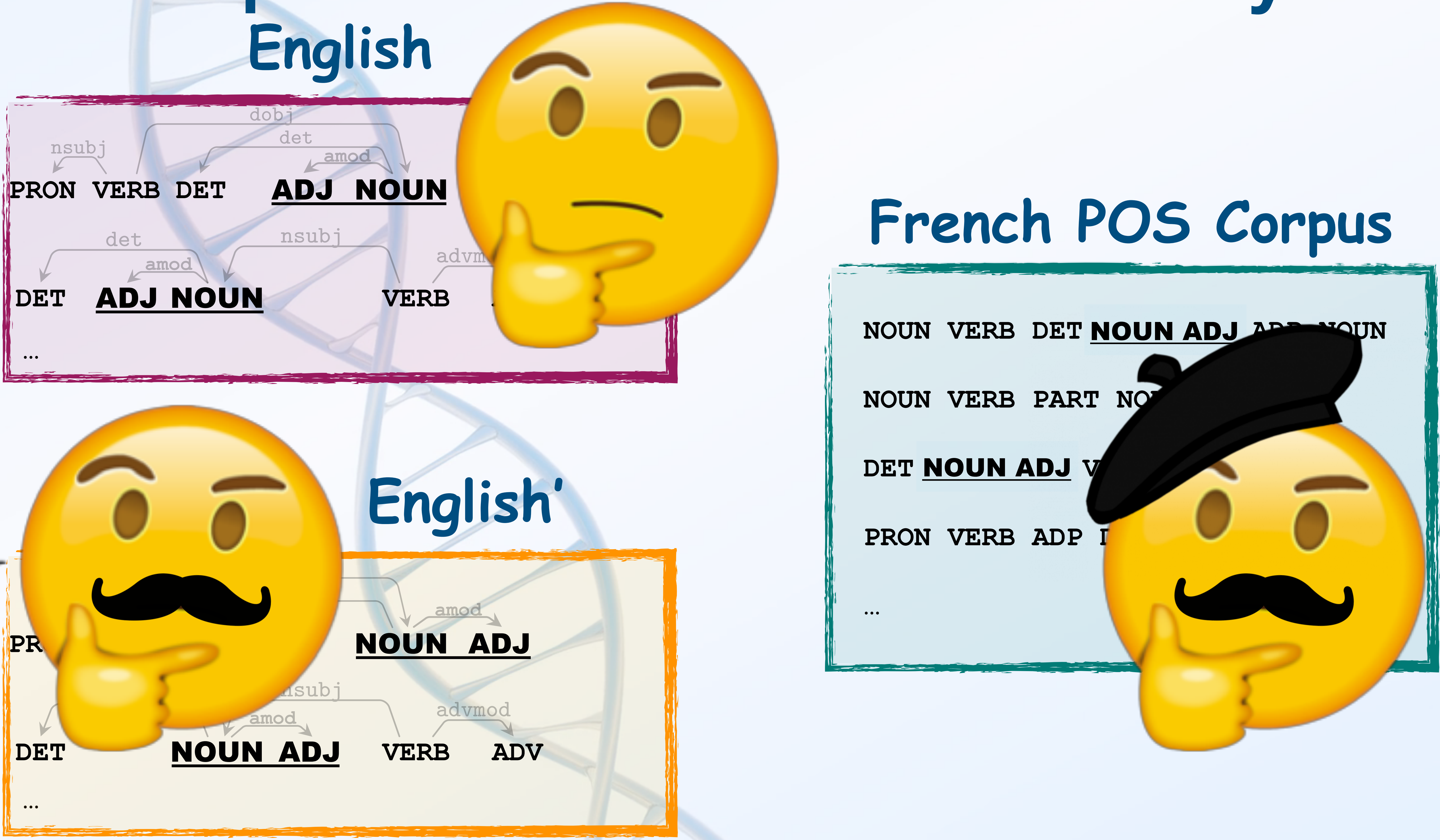
PRON VERB ADP I…

…

Improve the surface similarity



Improve the surface similarity

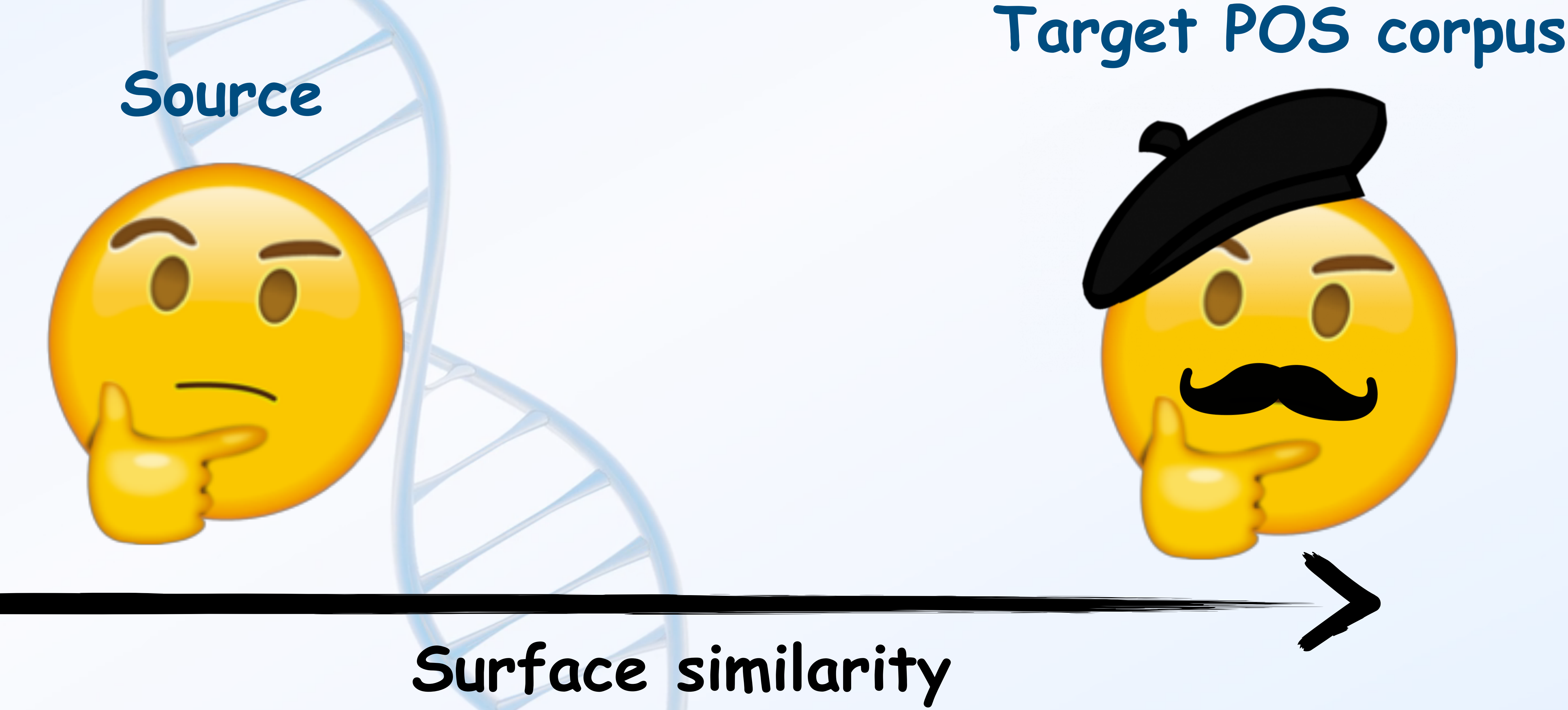


Improve the surface similarity

Target POS corpus

Source

Improve the surface similarity



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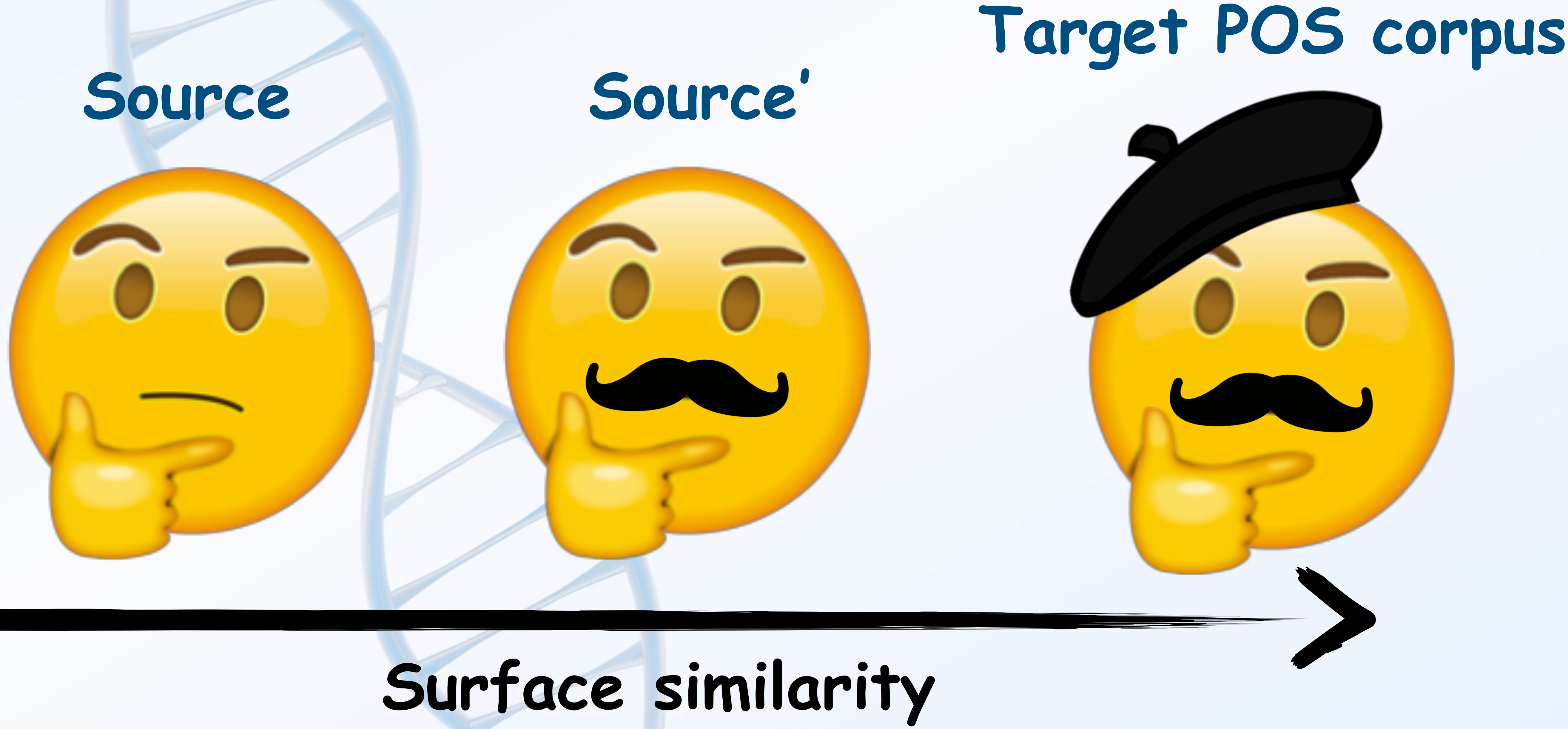
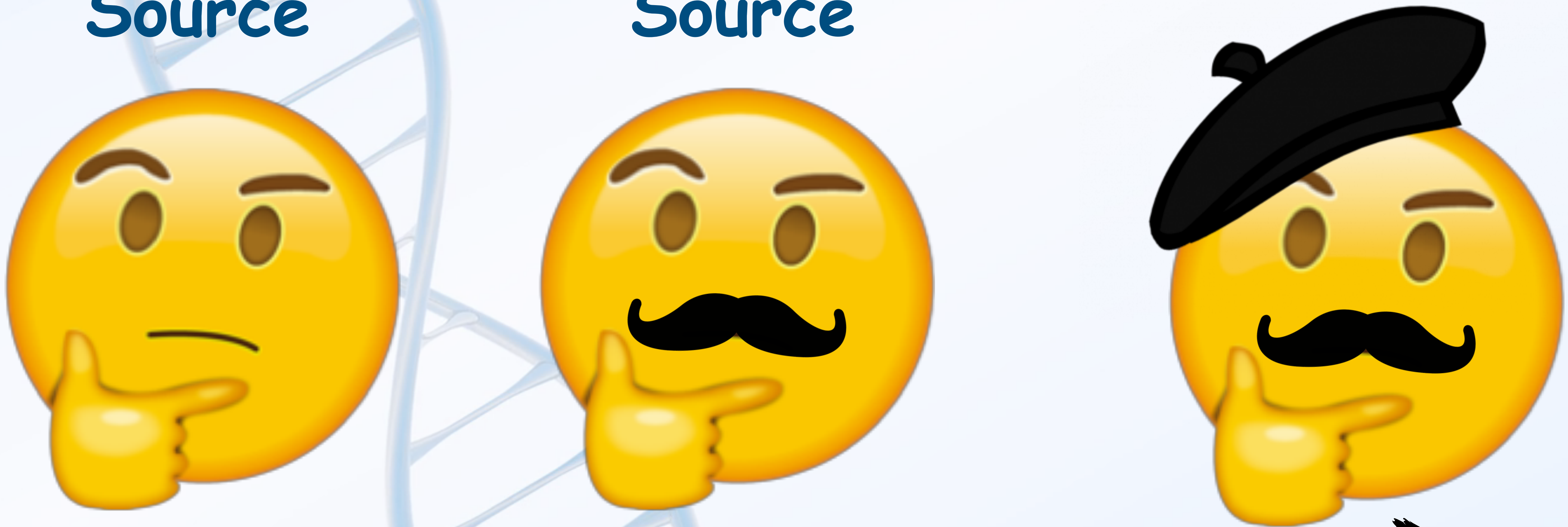


Improve the surface similarity

Source

Source'

Target POS corpus



Surface similarity

Transfer Parsing accuracy?

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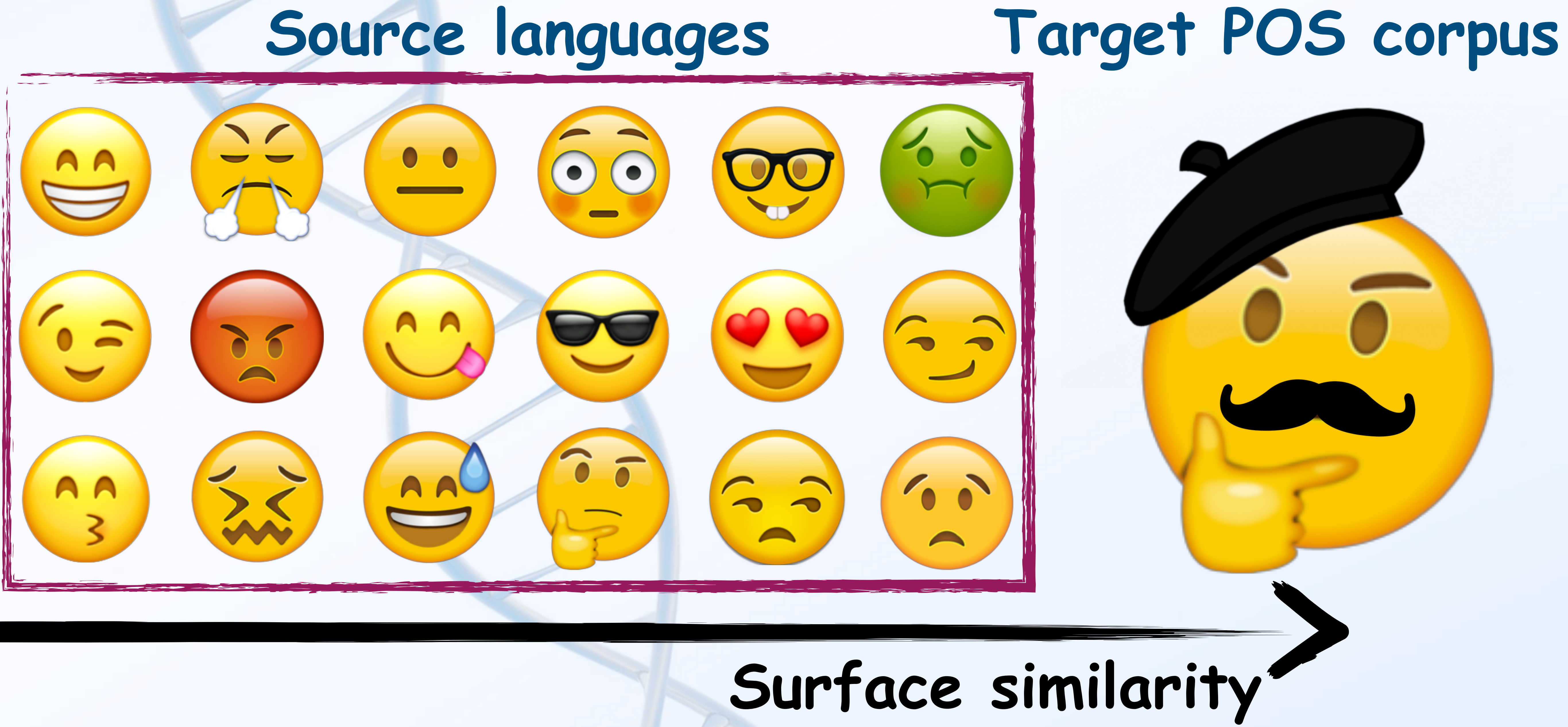
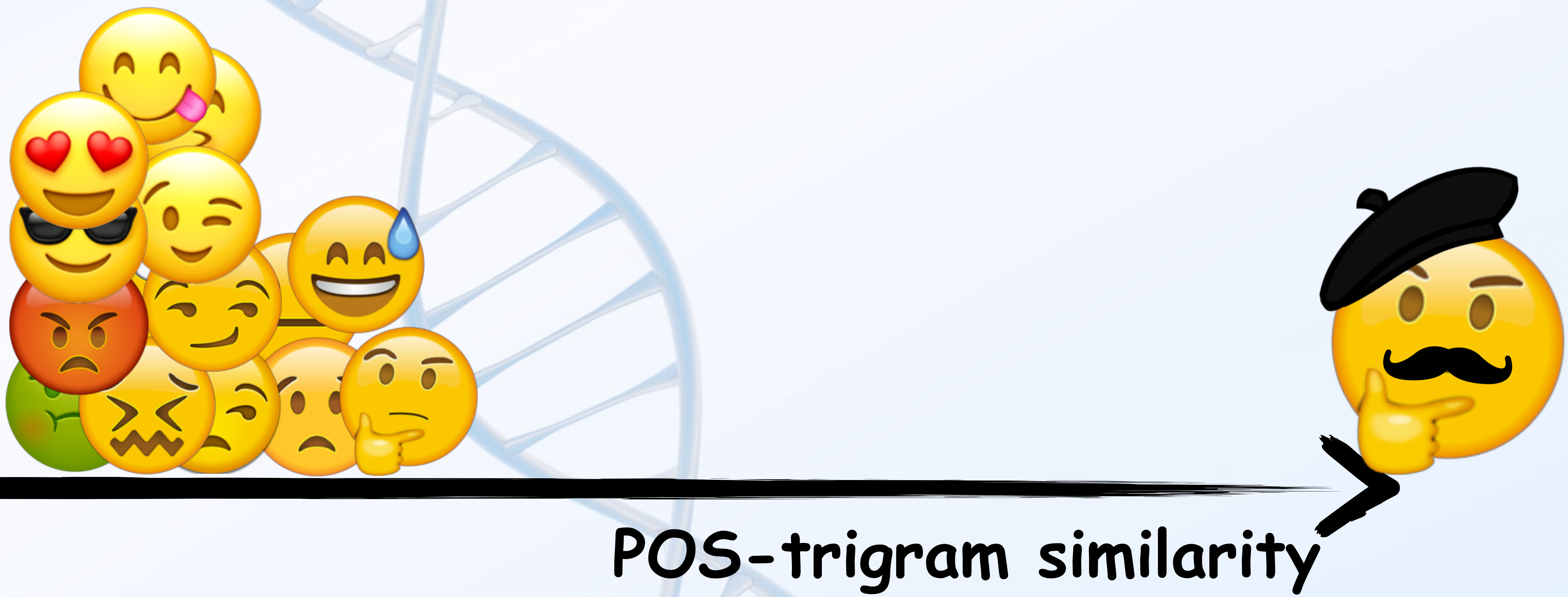
Single-Source Selection



Single-Source Selection

Source languages

Target POS corpus



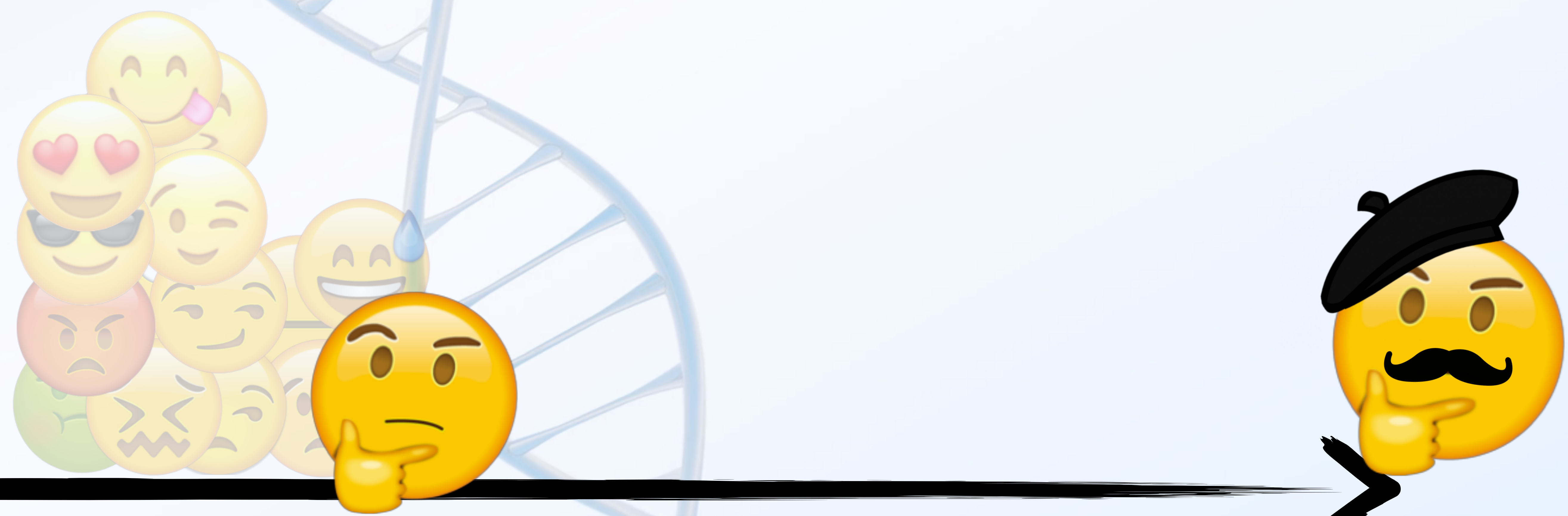
Single-Source Selection

Source languages **Target POS corpus**

POS-trigram similarity

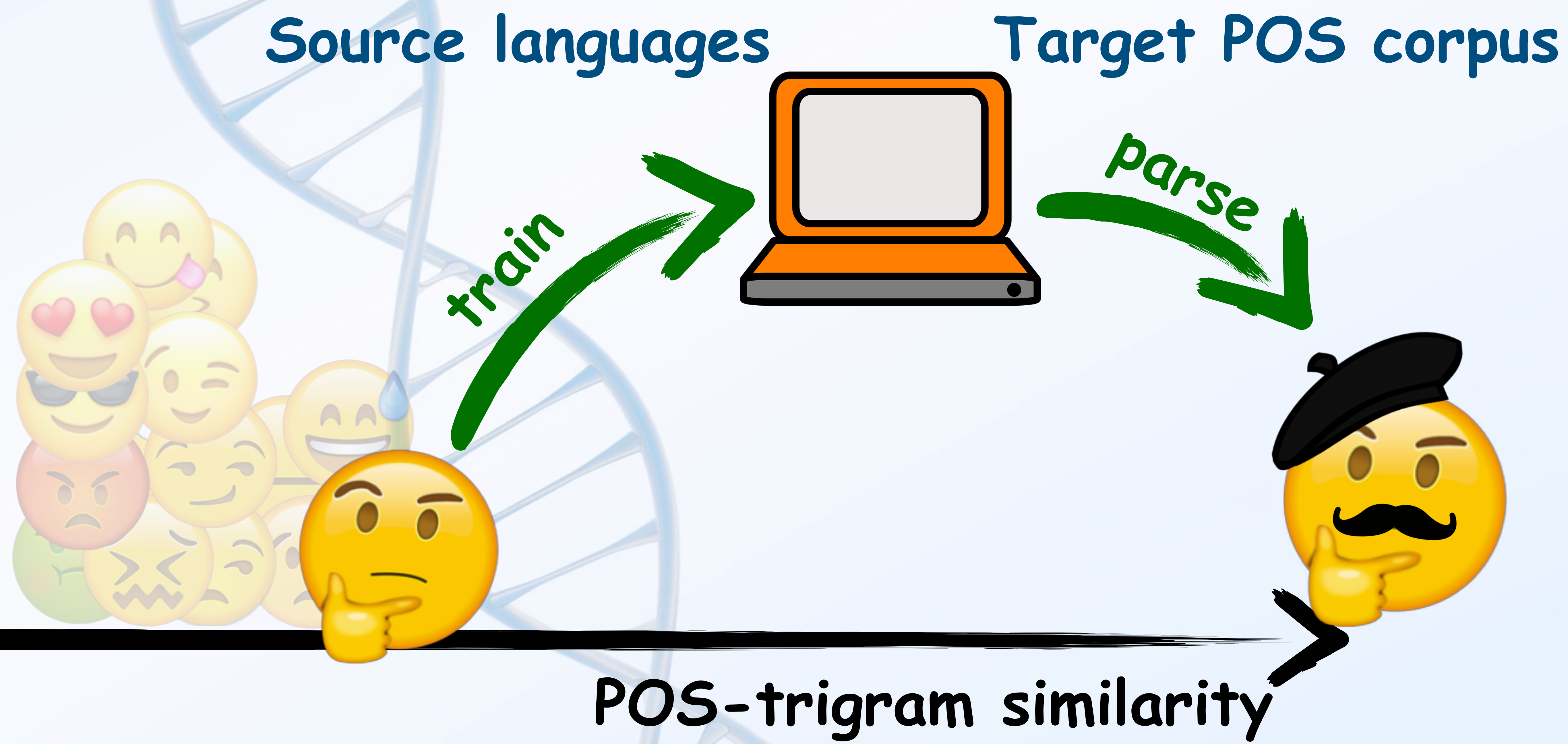
Single-Source Selection

Source languages **Target POS corpus**



POS-trigram similarity

Single-Source Selection

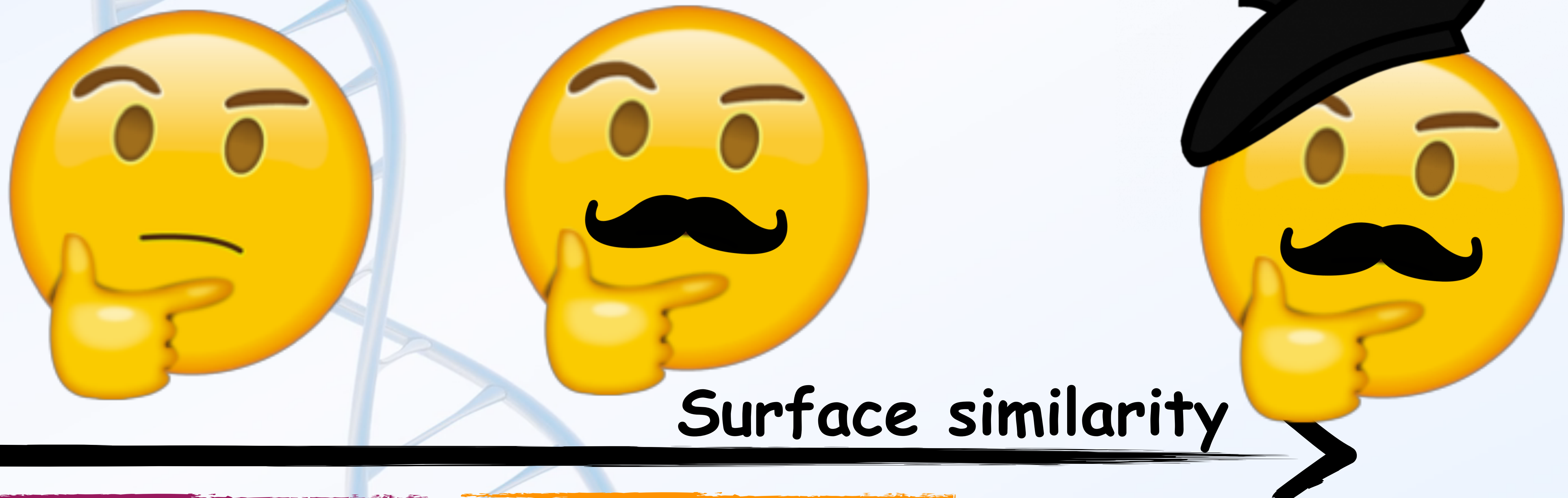


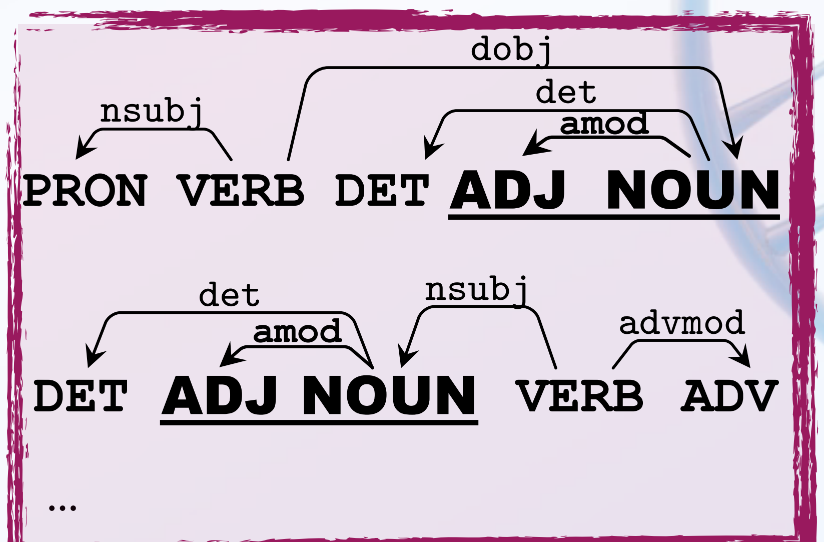
Synthetic Data

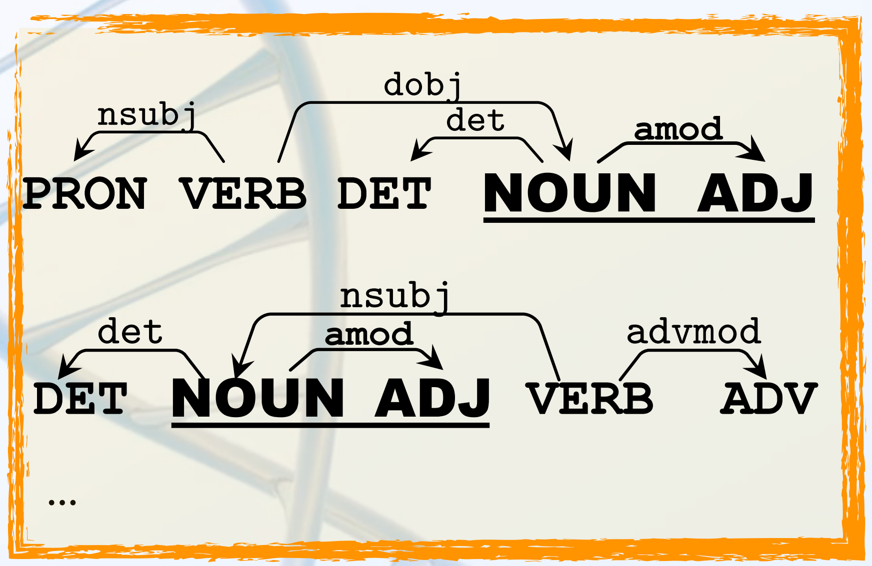
Source

Source'

Target POS corpus







NOUN VERB DET **NOUN ADJ**

NOUN VERB PART NOUN

DET **NOUN ADJ** VERB

PRON VERB ADP DET NOUN

...

Synthetic Data

Source

Synthetic Source'

Target POS corpus

Surface similarity

dobj
nsubj det
amod
PRON VERB DET **ADJ NOUN**

det nsubj
amod advmod
DET **ADJ NOUN** VERB ADV

...

dobj
nsubj det amod
PRON VERB DET **NOUN ADJ**

nsubj
det amod advmod
DET **NOUN ADJ** VERB ADV

...

NOUN VERB DET **NOUN ADJ**

NOUN VERB PART NOUN

DET **NOUN ADJ** VERB

PRON VERB ADP DET NOUN

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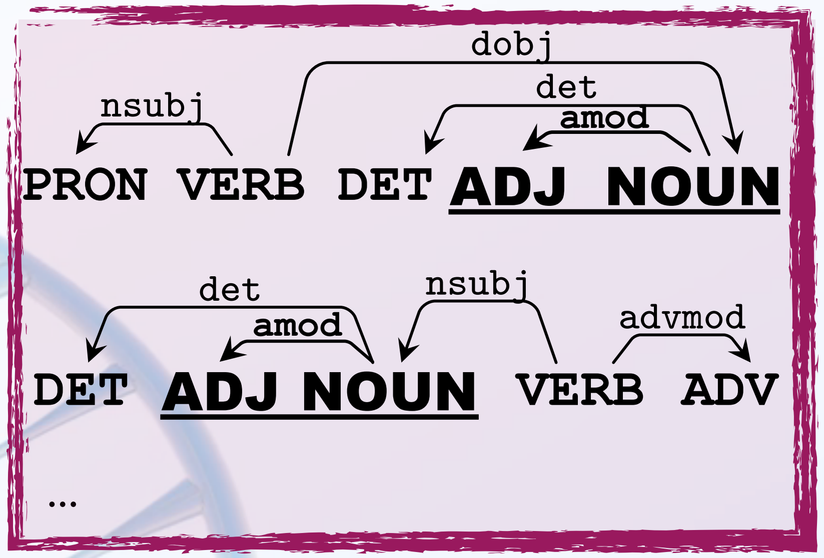
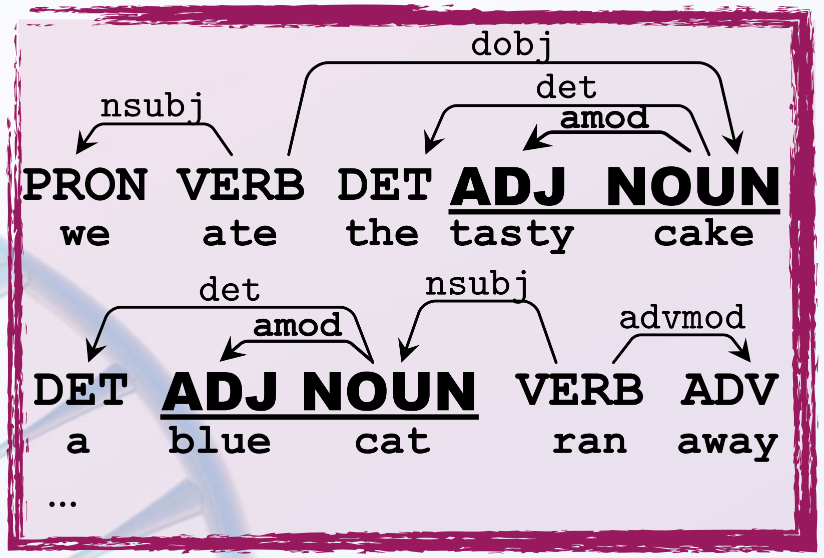
Synthetic Data

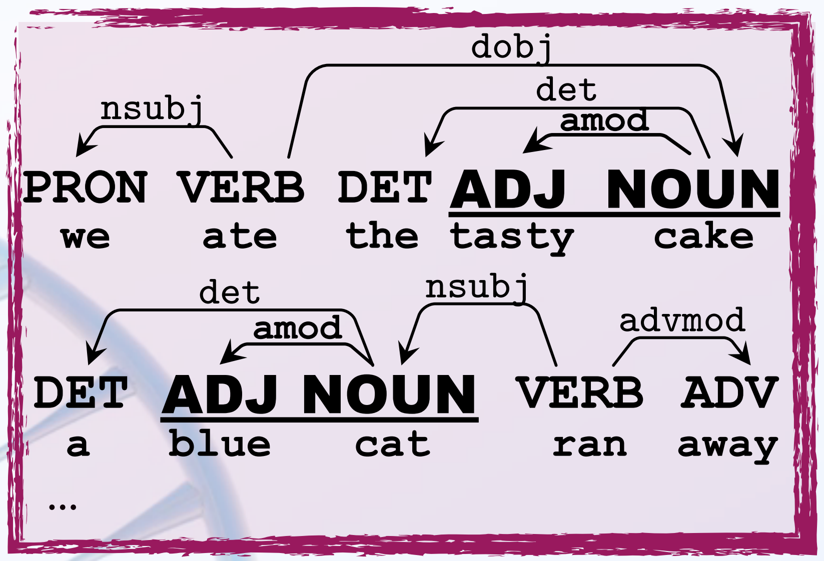


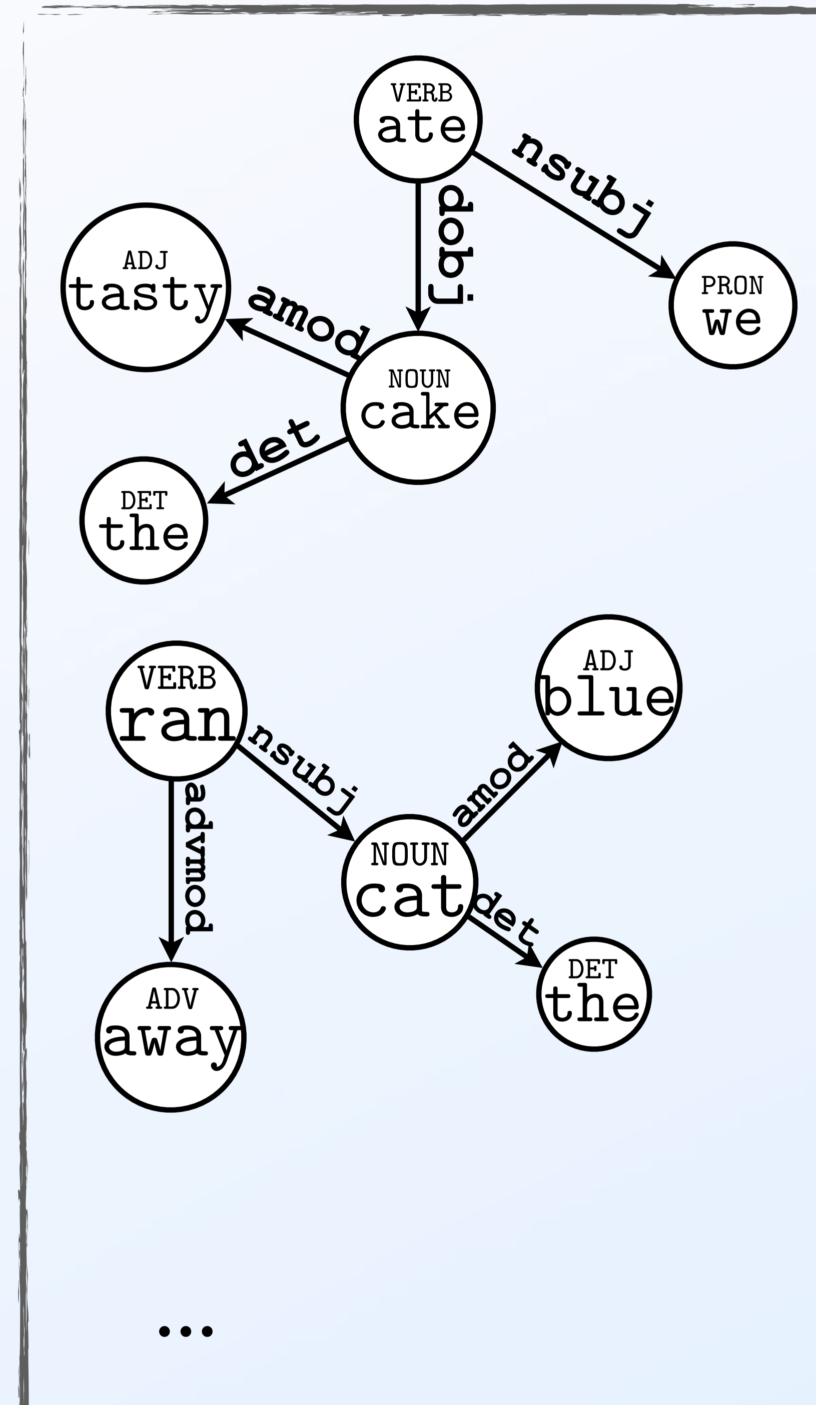
Synthetic Data



Synthetic Data

Unordered dep.





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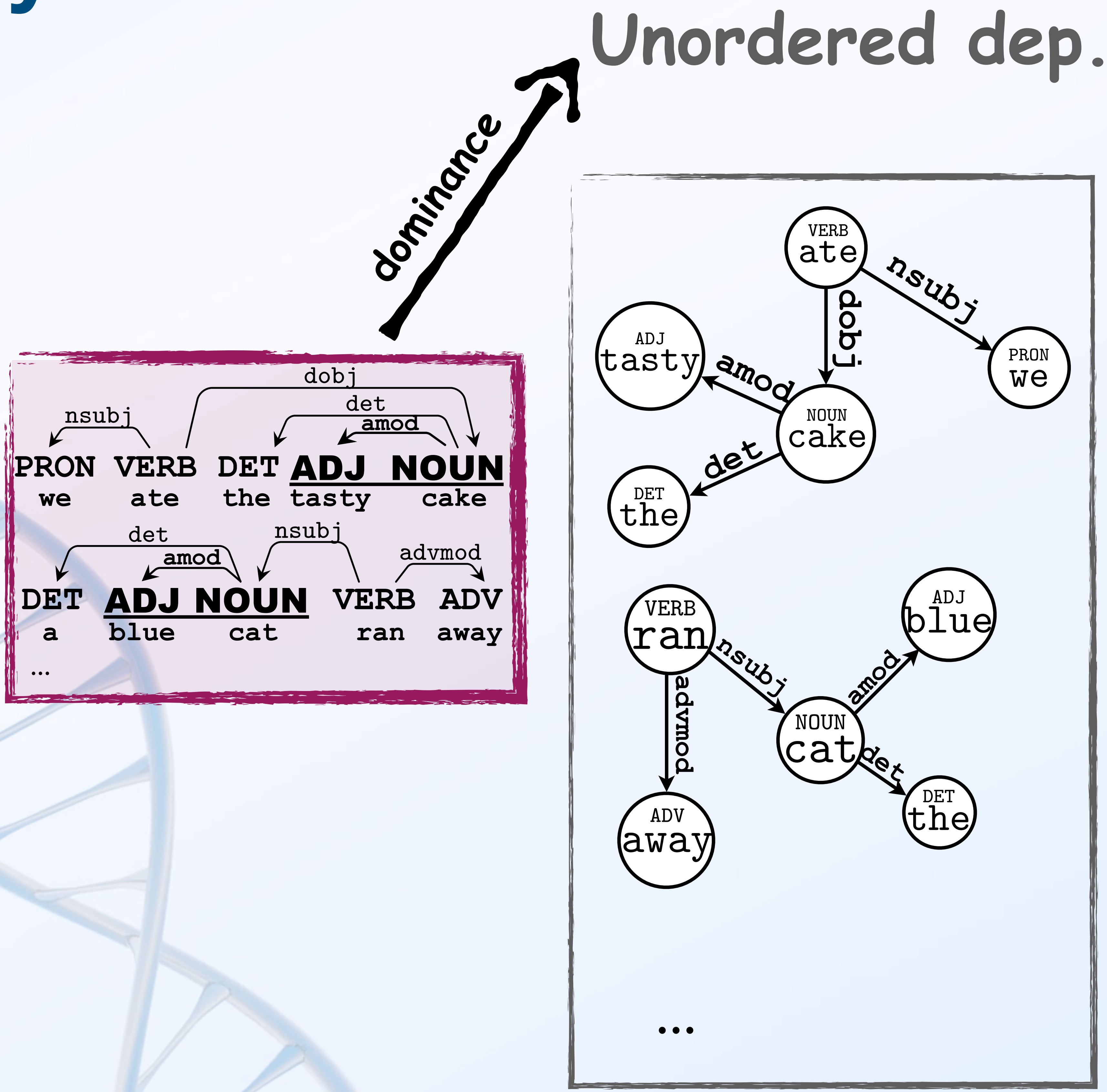


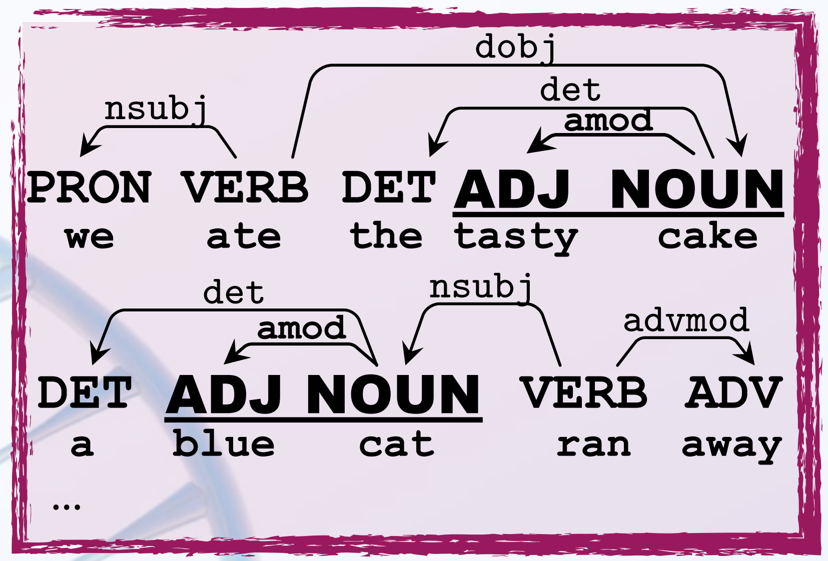
Synthetic Data

Surface order

PRON VERB DET **ADJ NOUN**
we ate the tasty cake

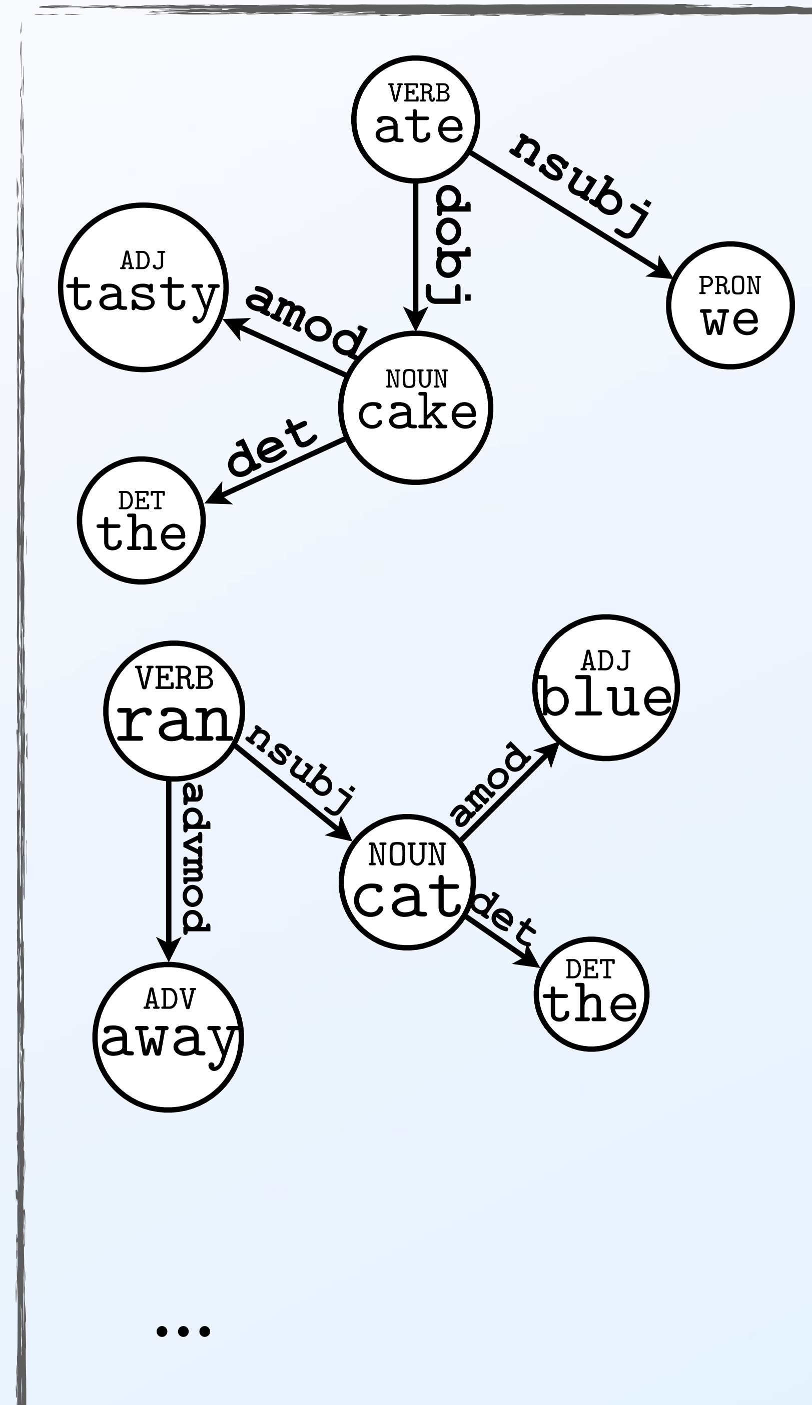
DET **ADJ NOUN** VERB ADV
a blue cat ran away

…



dominance

Unordered dep.



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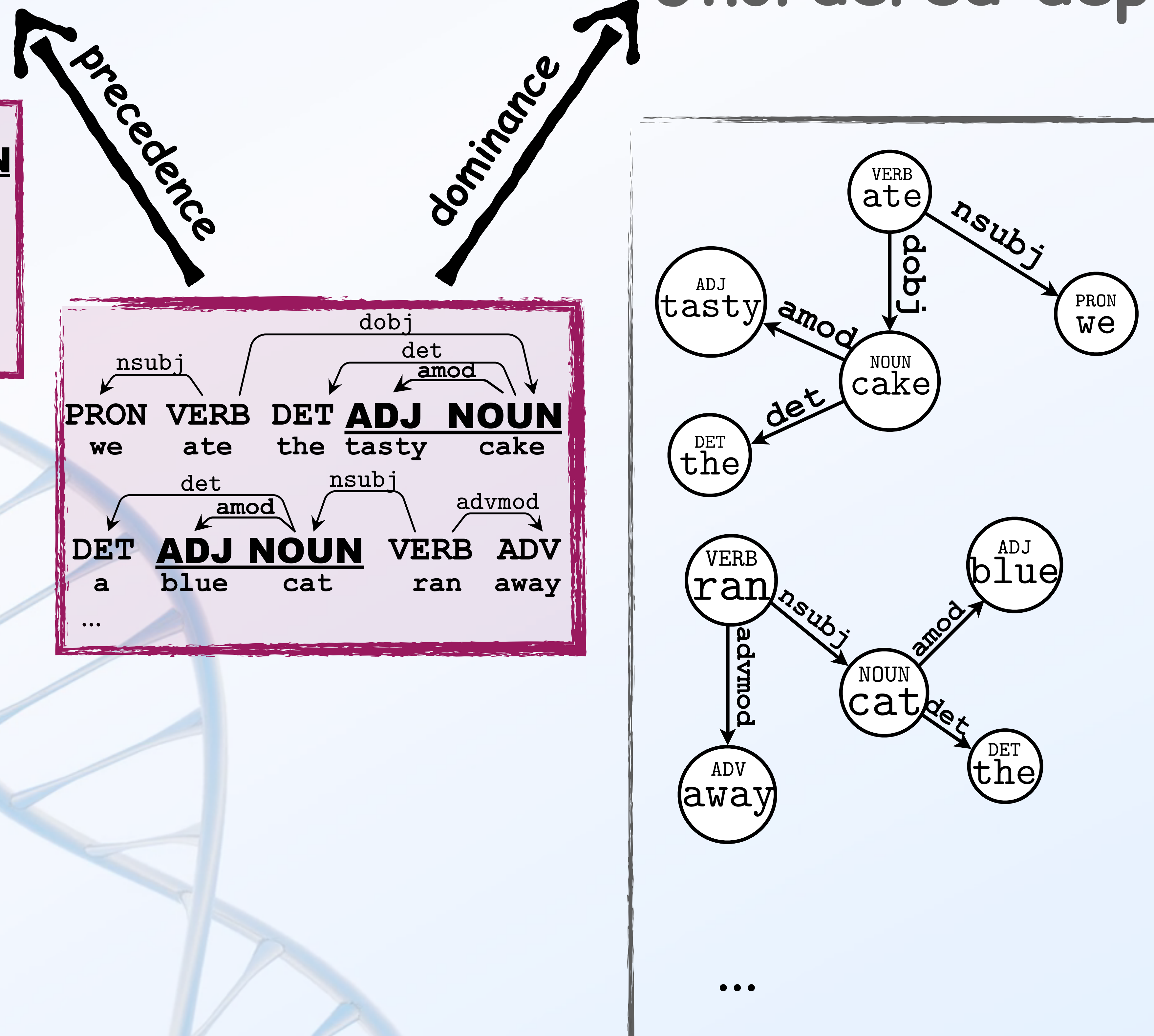
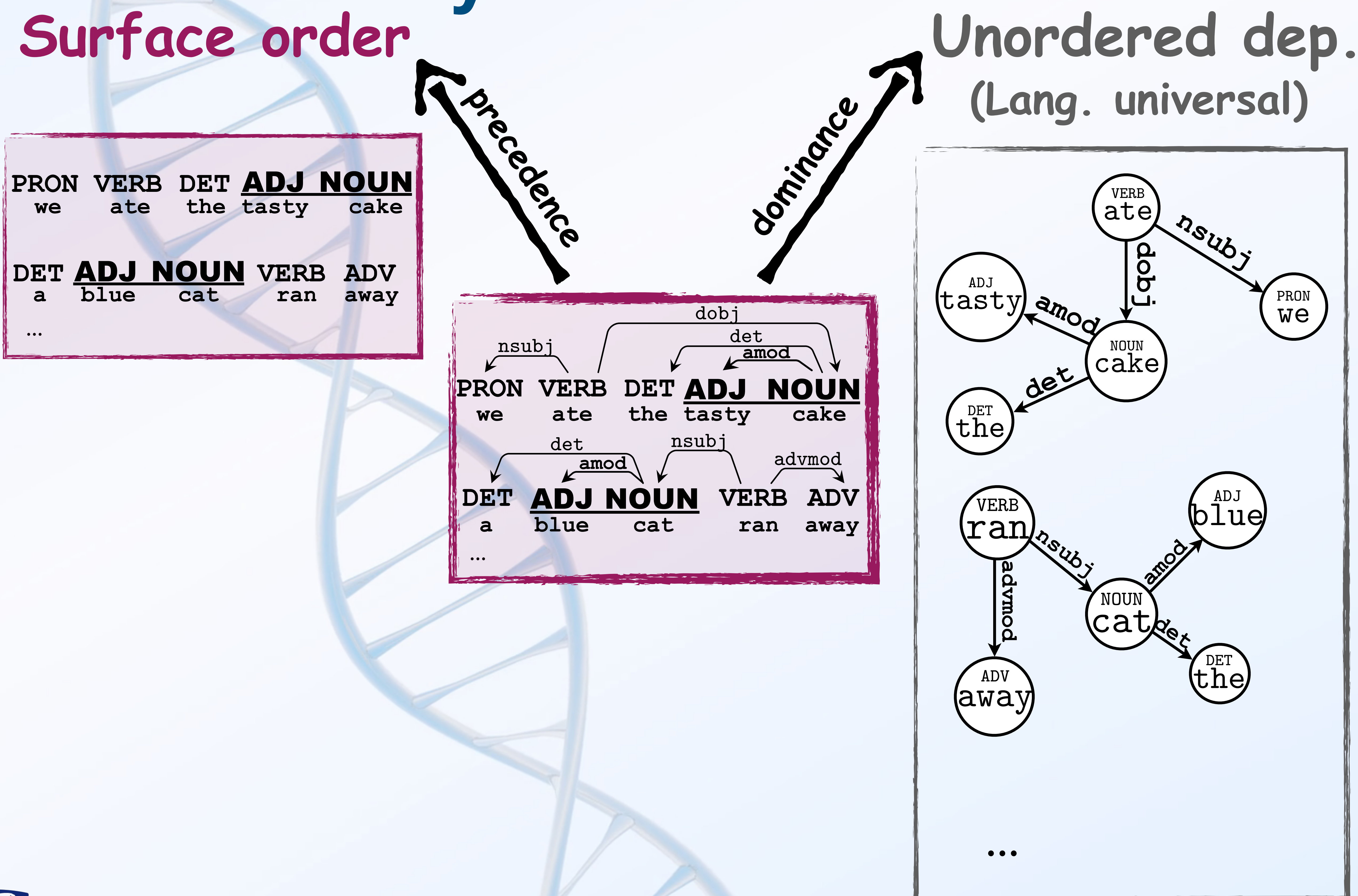
Unordered dep.



Synthetic Data



Synthetic Data

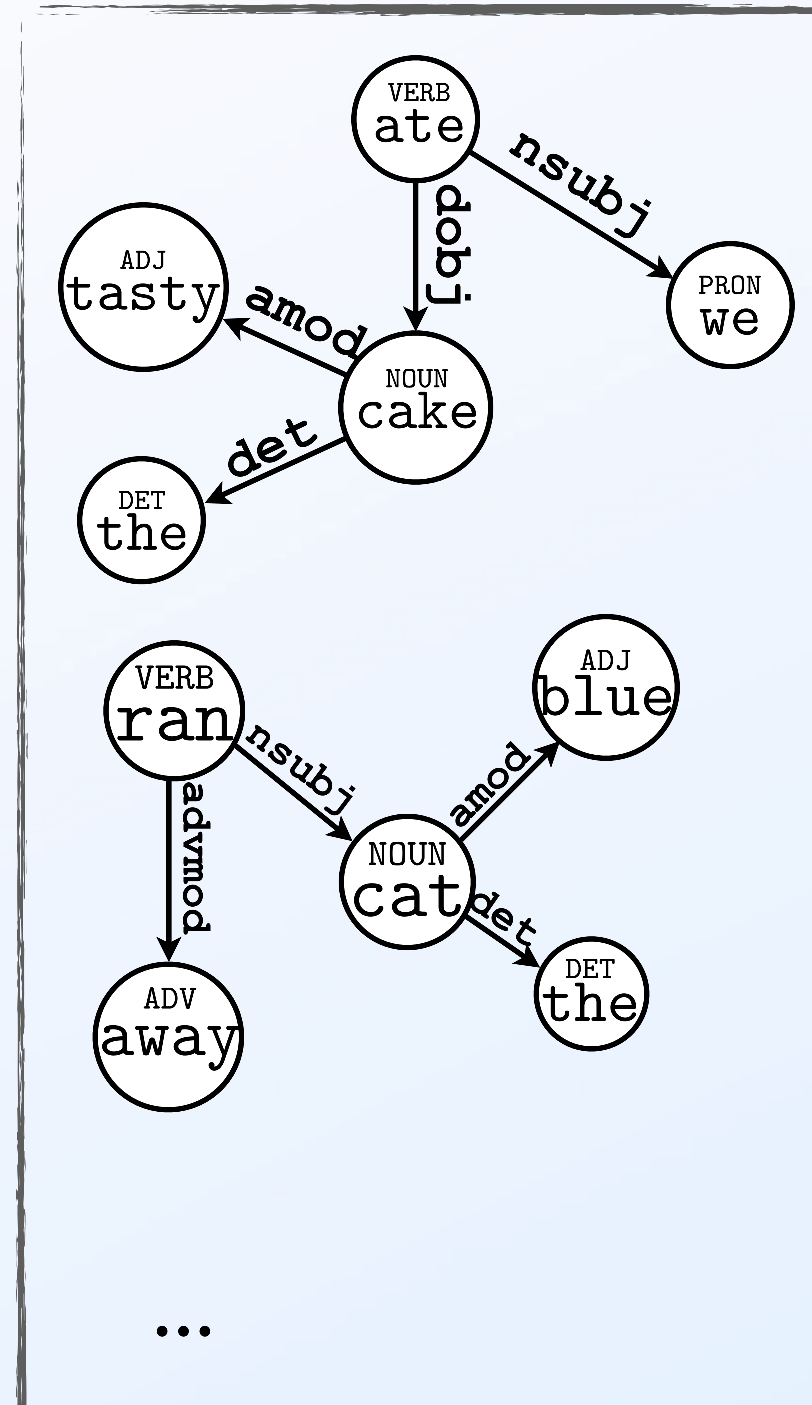
Surface order
(Lang. specific)

PRON VERB DET **<u>ADJ NOUN</u>**
we ate the tasty cake

DET **<u>ADJ NOUN</u>** VERB ADV
a blue cat ran away

…

Unordered dep.
(Lang. universal)



Synthetic Data

Surface order
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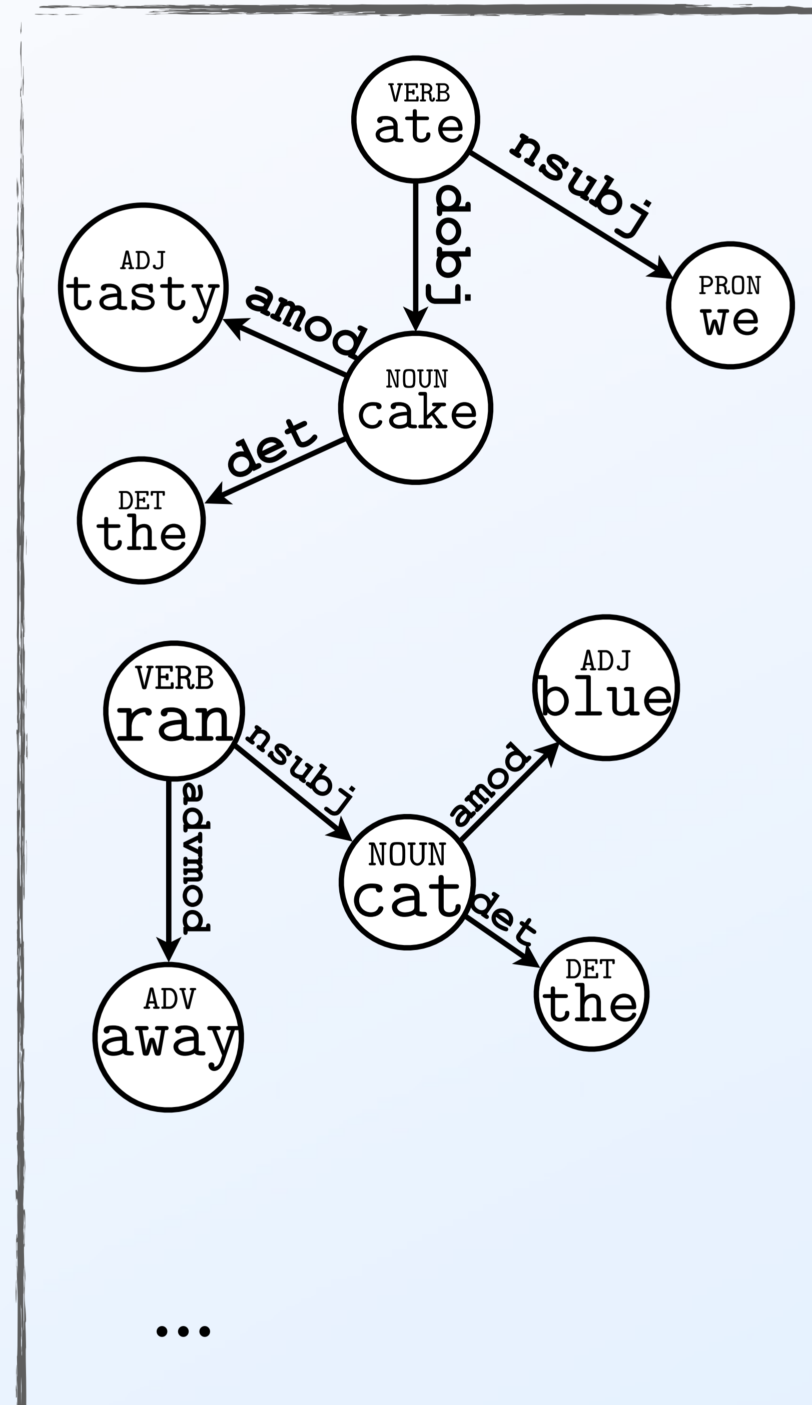
Parsing

Unordered dep.
(Lang. universal)



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(Lang. specific)

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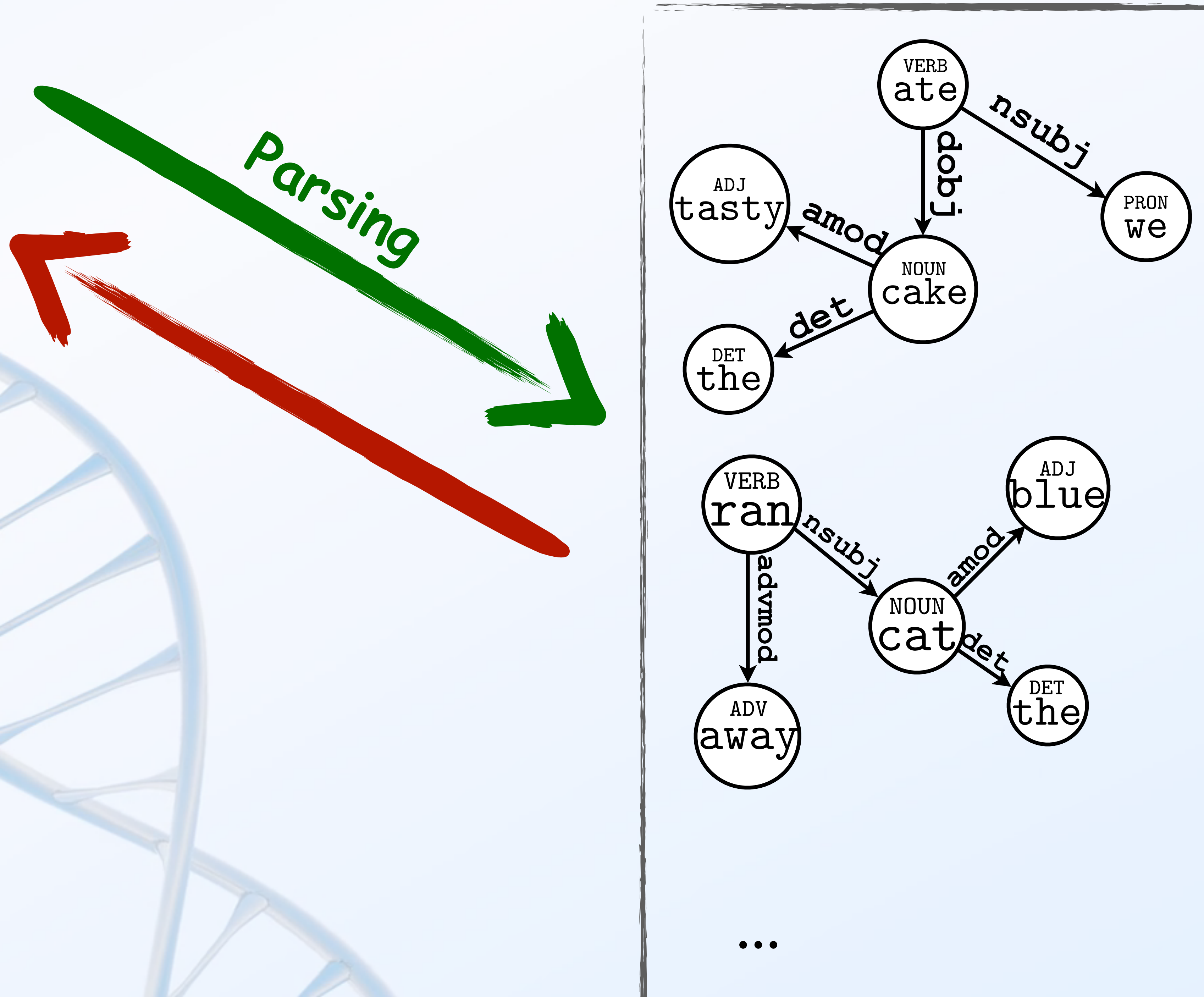

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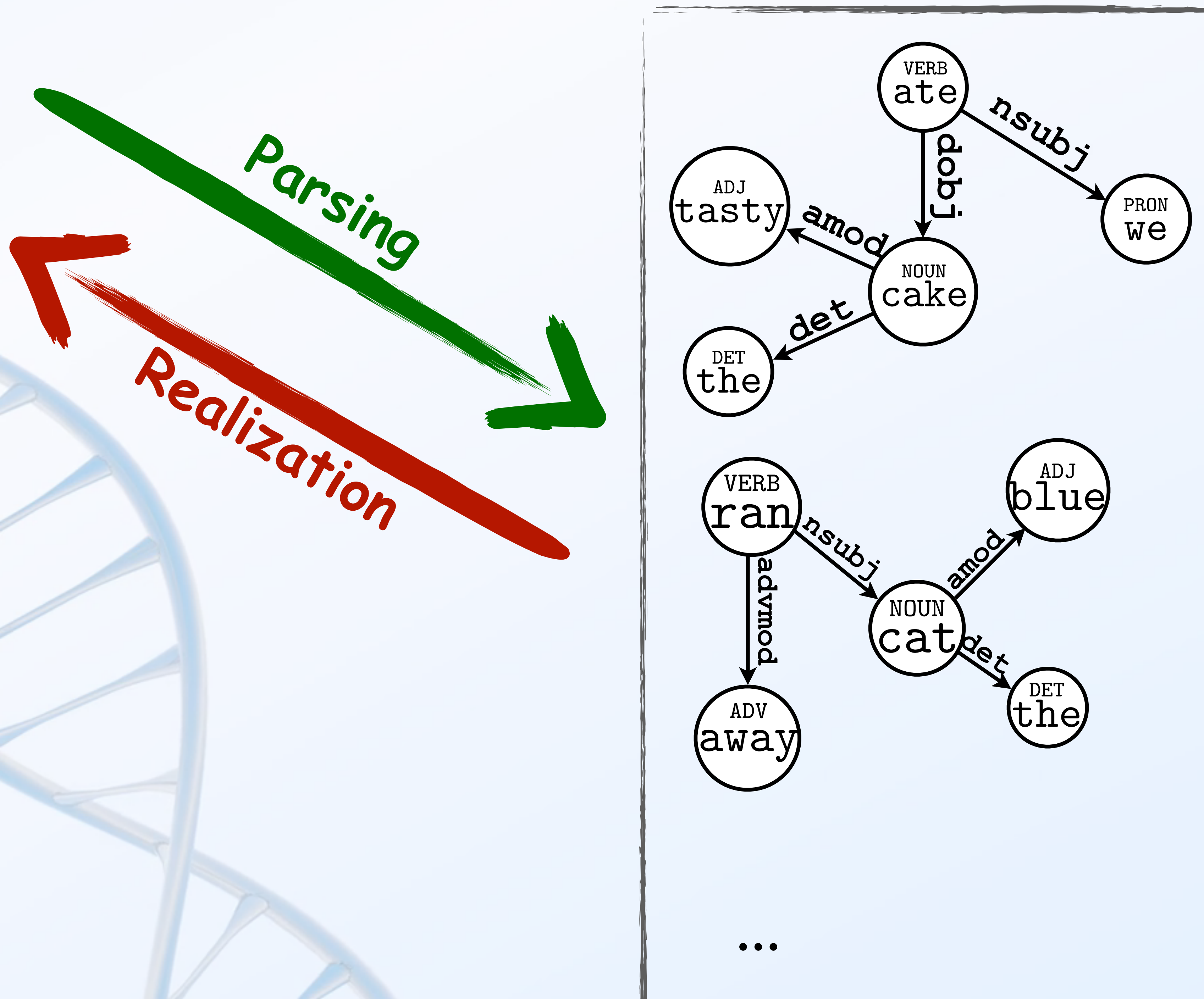

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Surface order
(Lang. specific)

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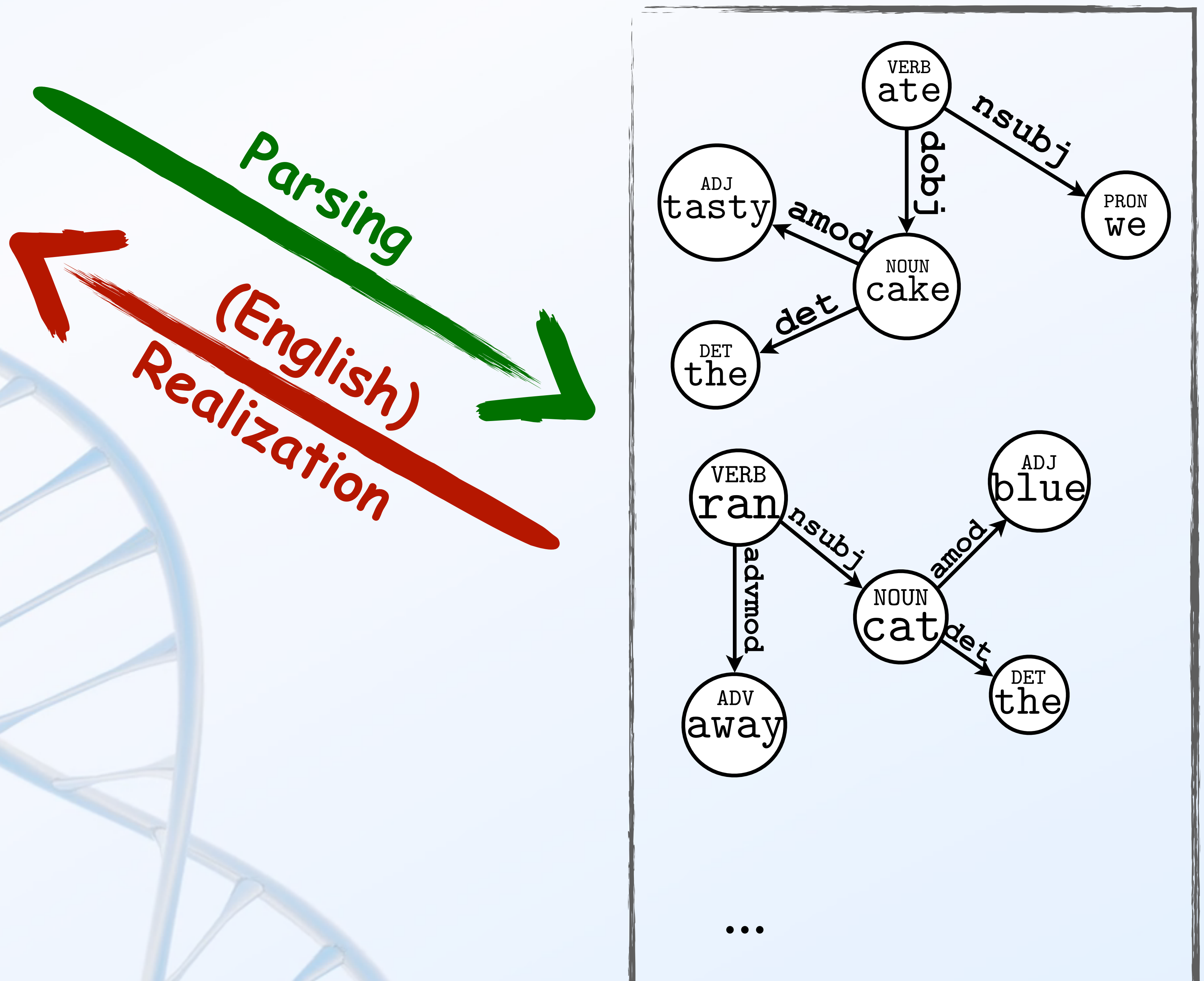

Synthetic Data

Surface order
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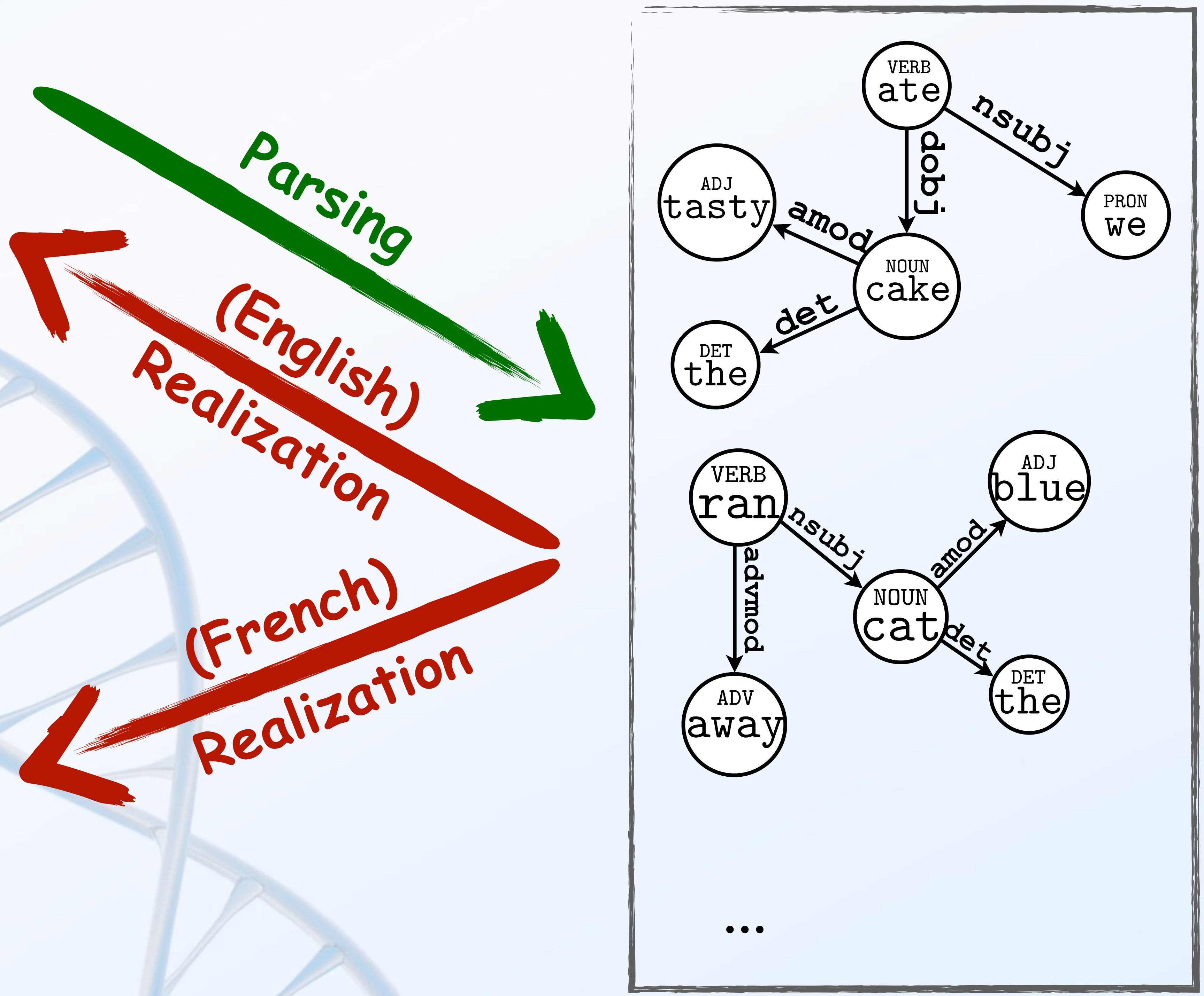
Unordered dep.
(Lang. universal)



PRON VERB DET **NOUN ADJ**
we ate the cake tasty

DET **NOUN ADJ** VERB ADV
a cat blue ran away

…

Synthetic Data

Surface order
(Lang. specific)

PRON VERB DET **ADJ NOUN**
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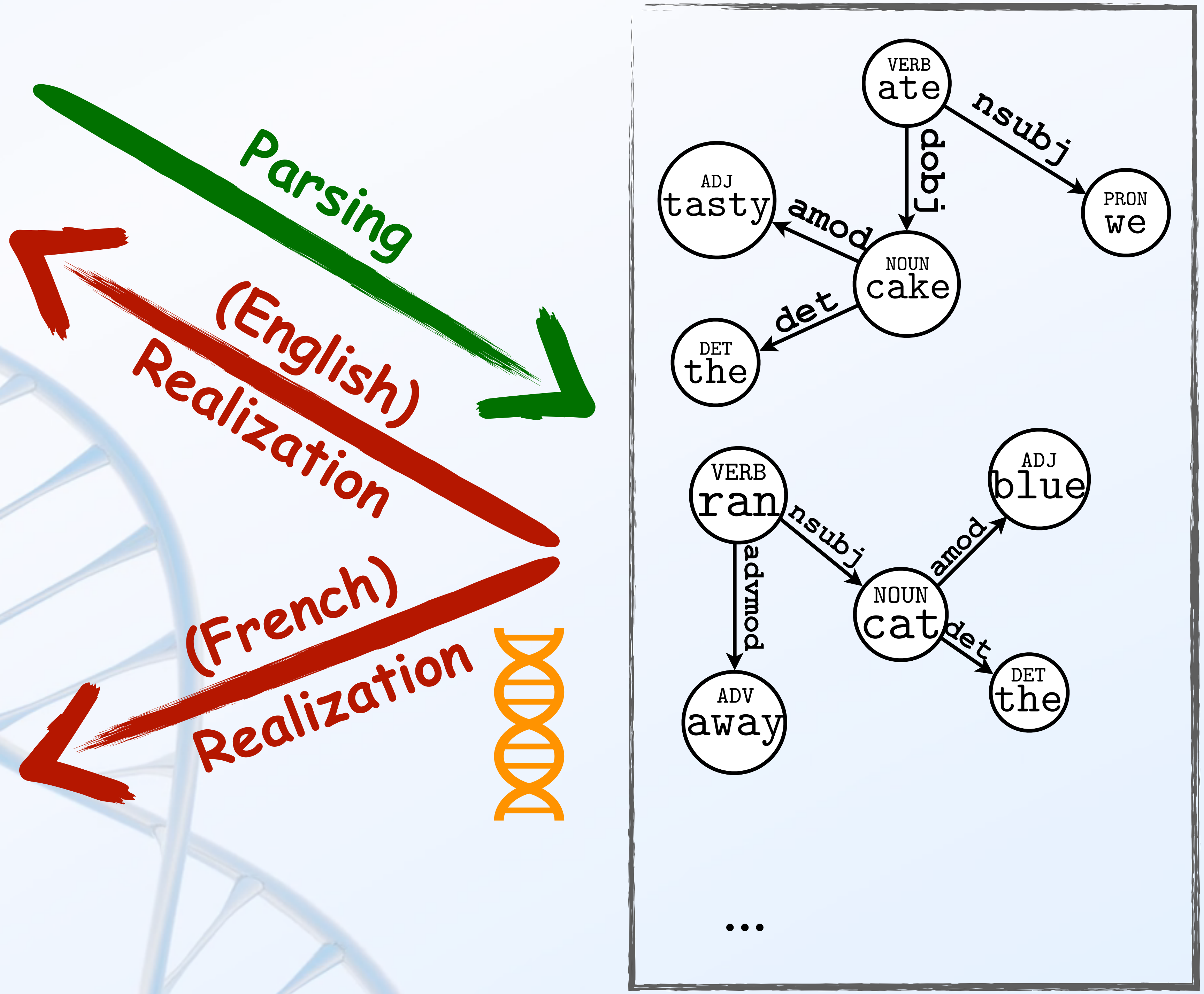

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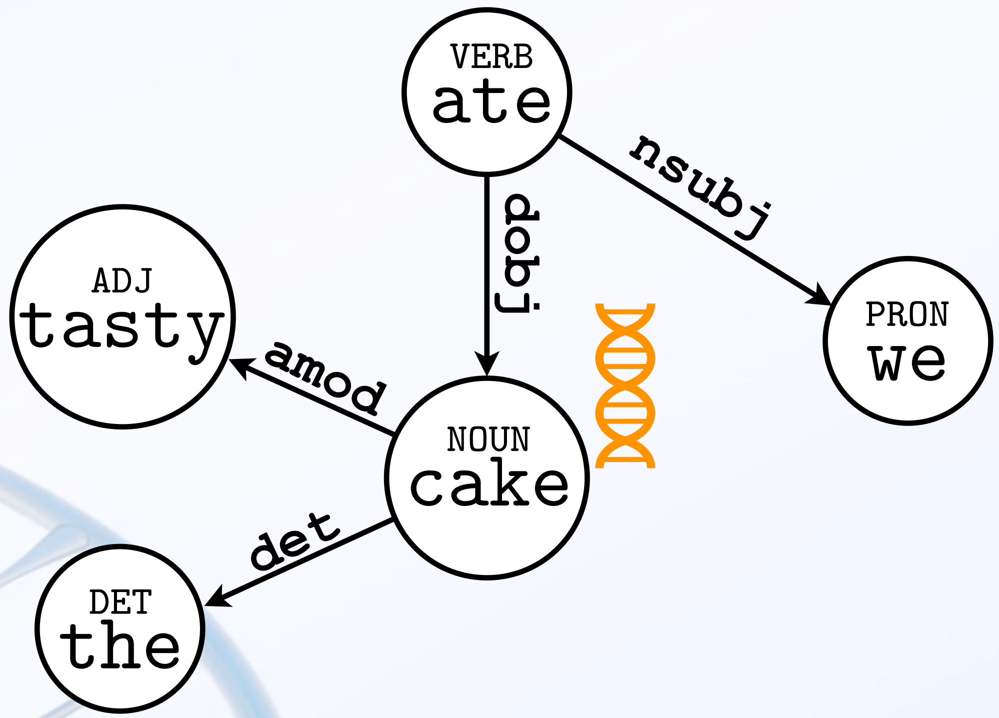
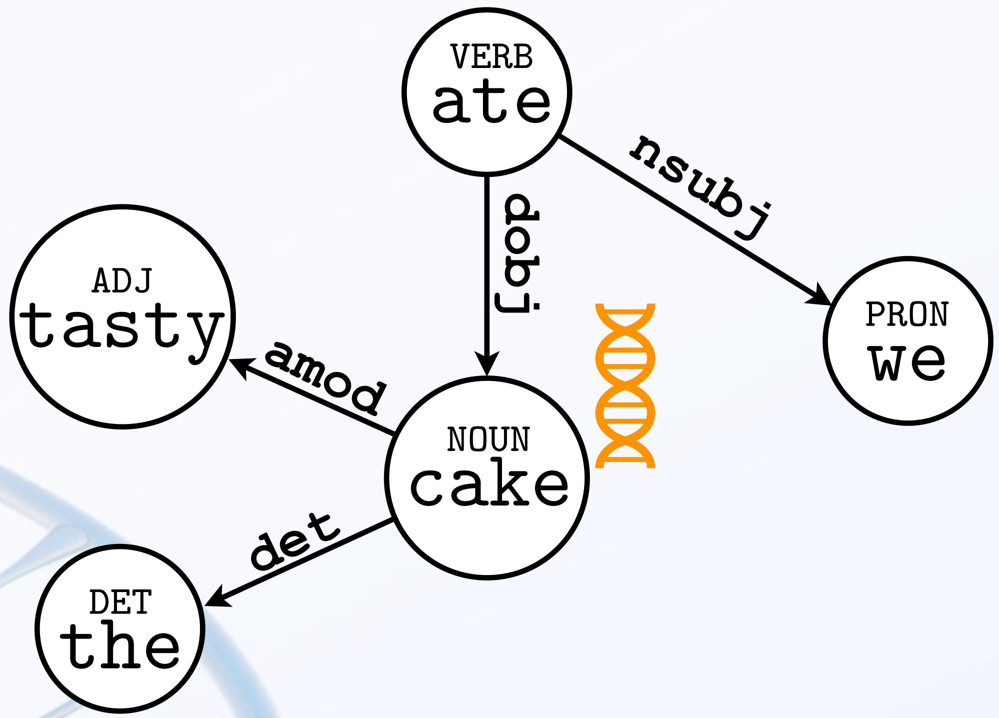
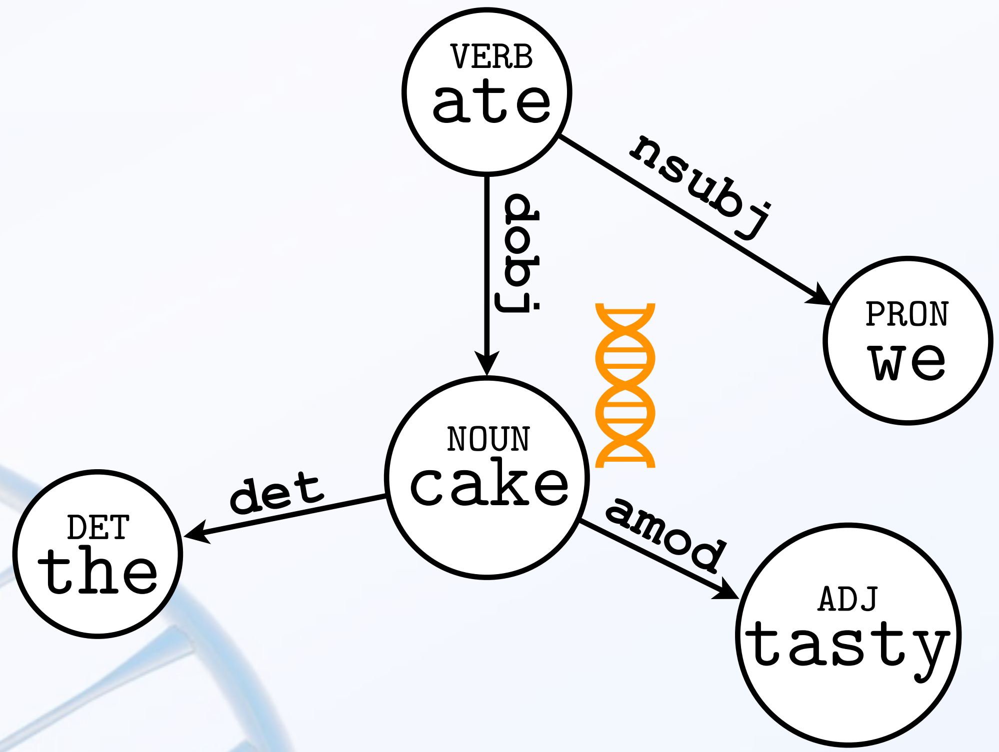
Surface Realization



Surface Realization



Surface Realization



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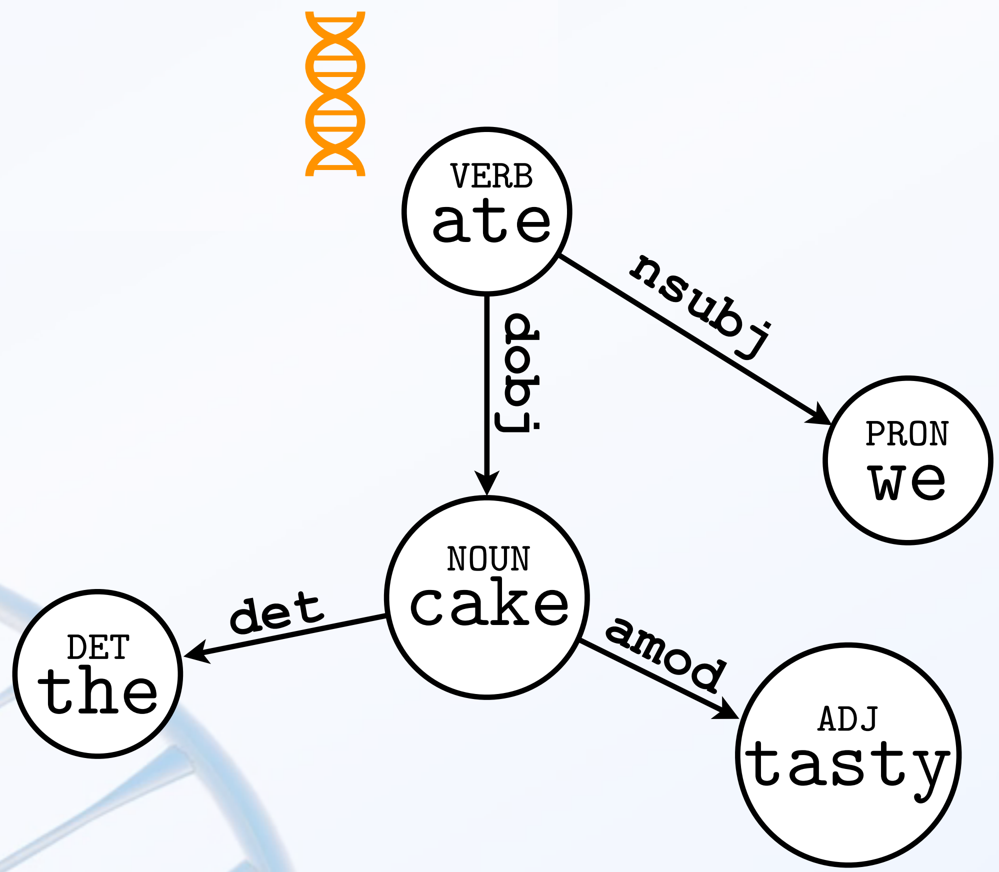
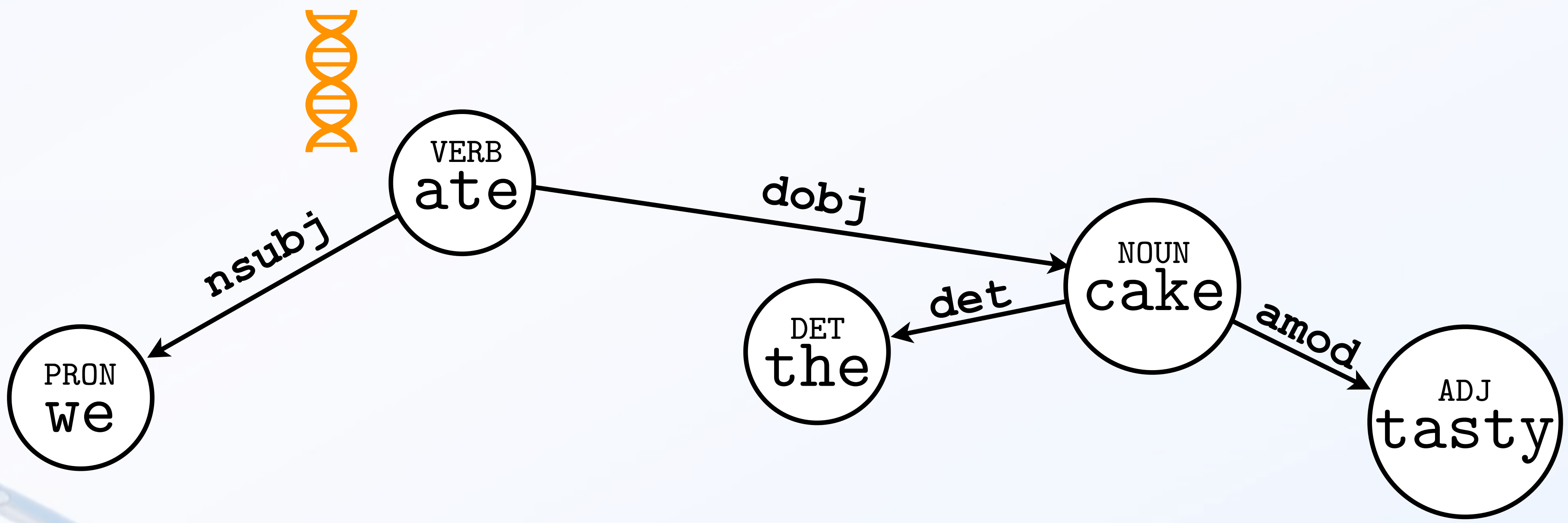


Surface Realization



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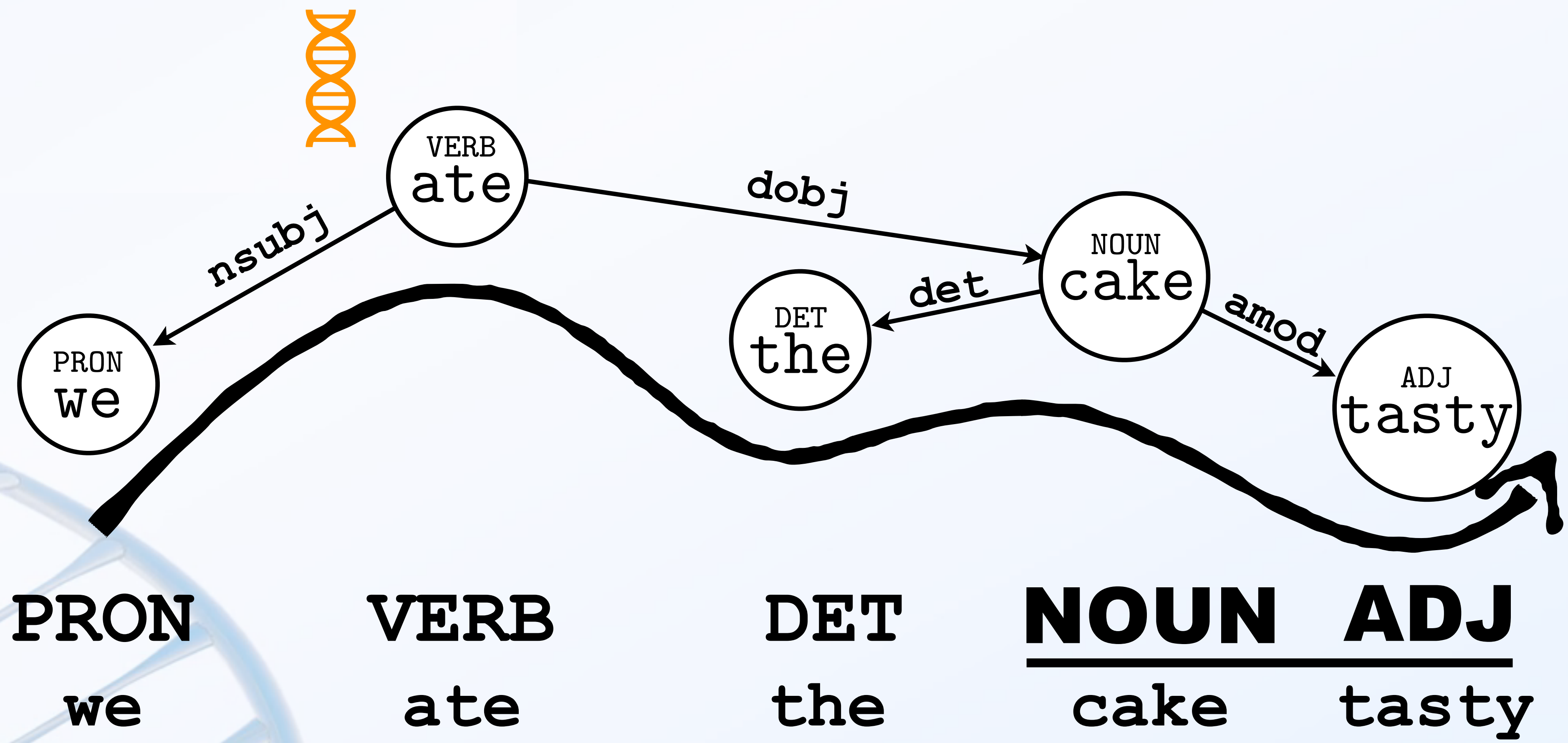
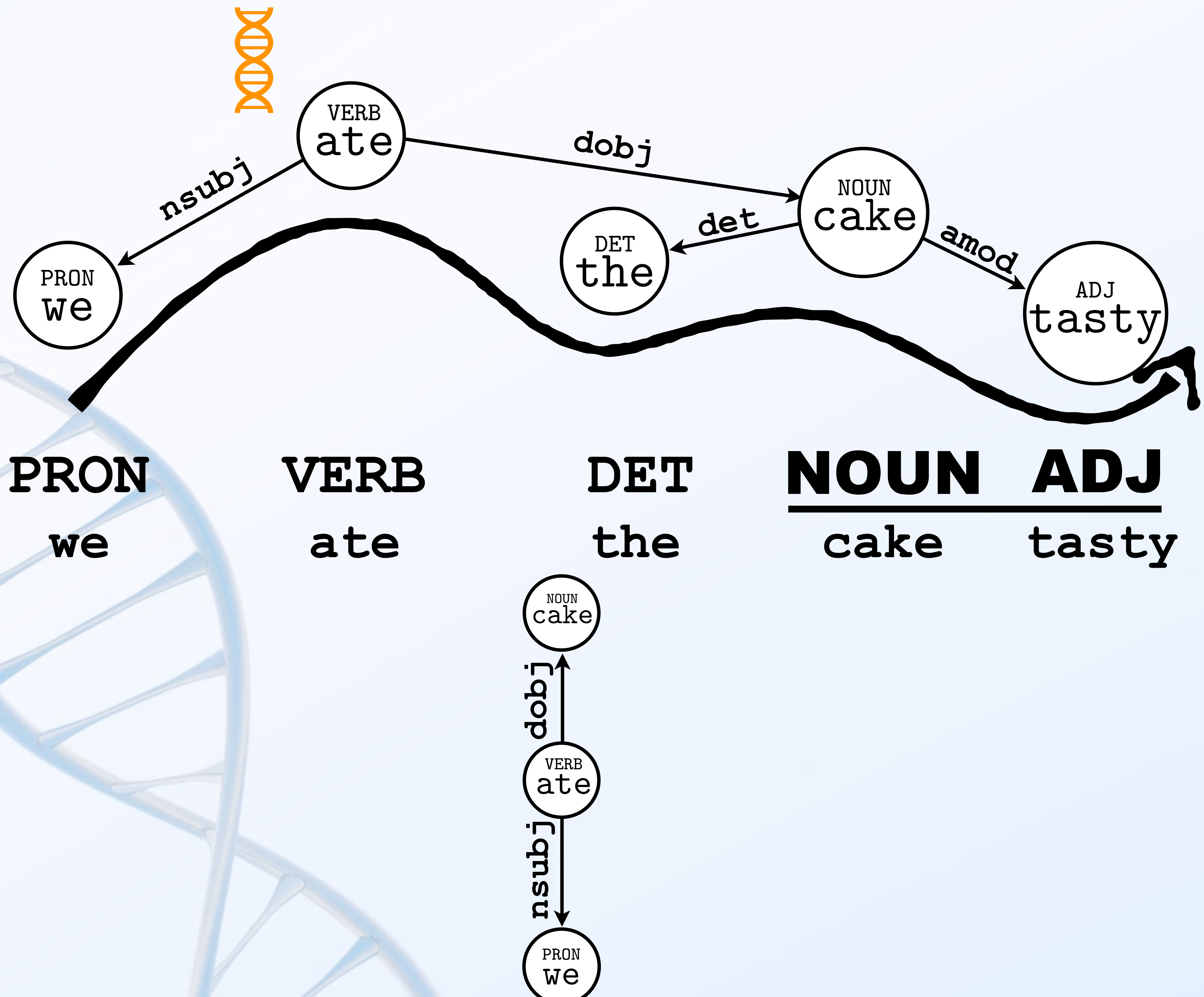
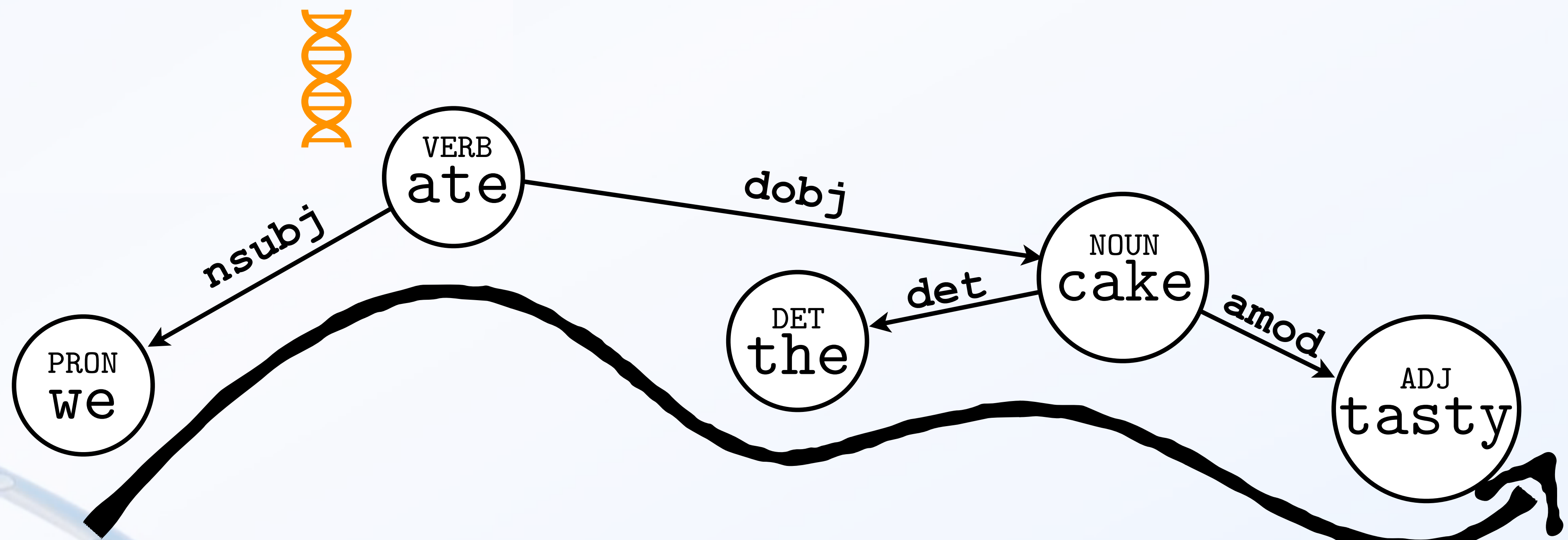
Surface Realization



Surface Realization



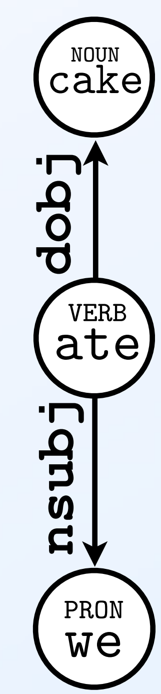
Surface Realization



PRON	VERB	DET	NOUN	ADJ
we	ate	the	cake	tasty

Loglinear model

$$p \left(\qquad \middle| \qquad \right)$$



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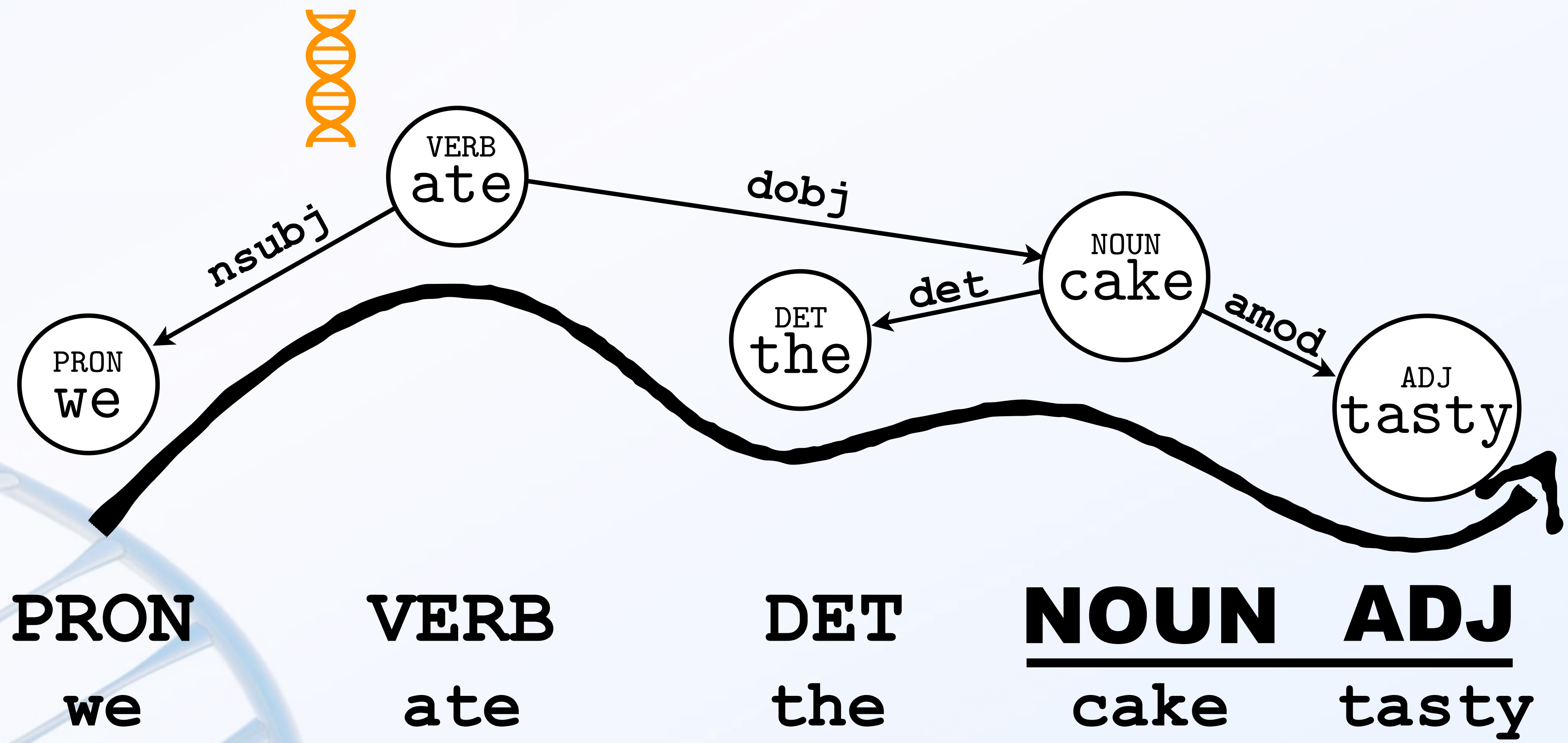
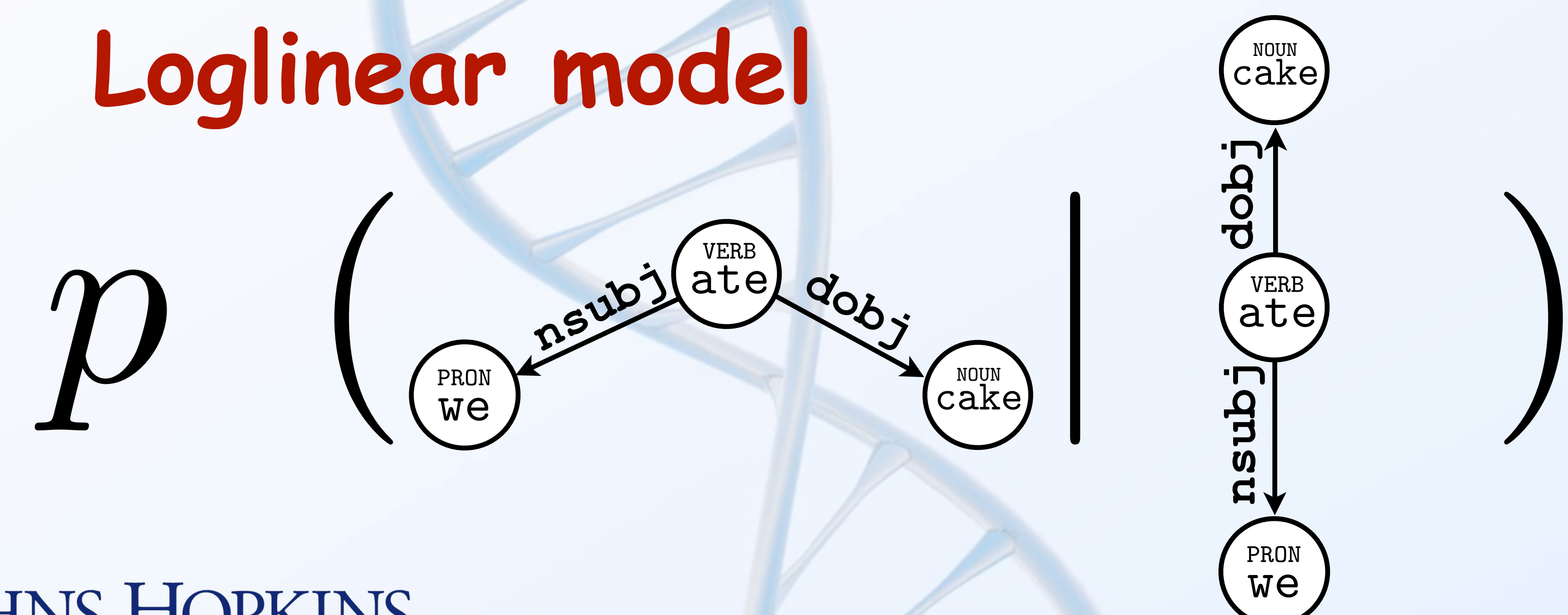
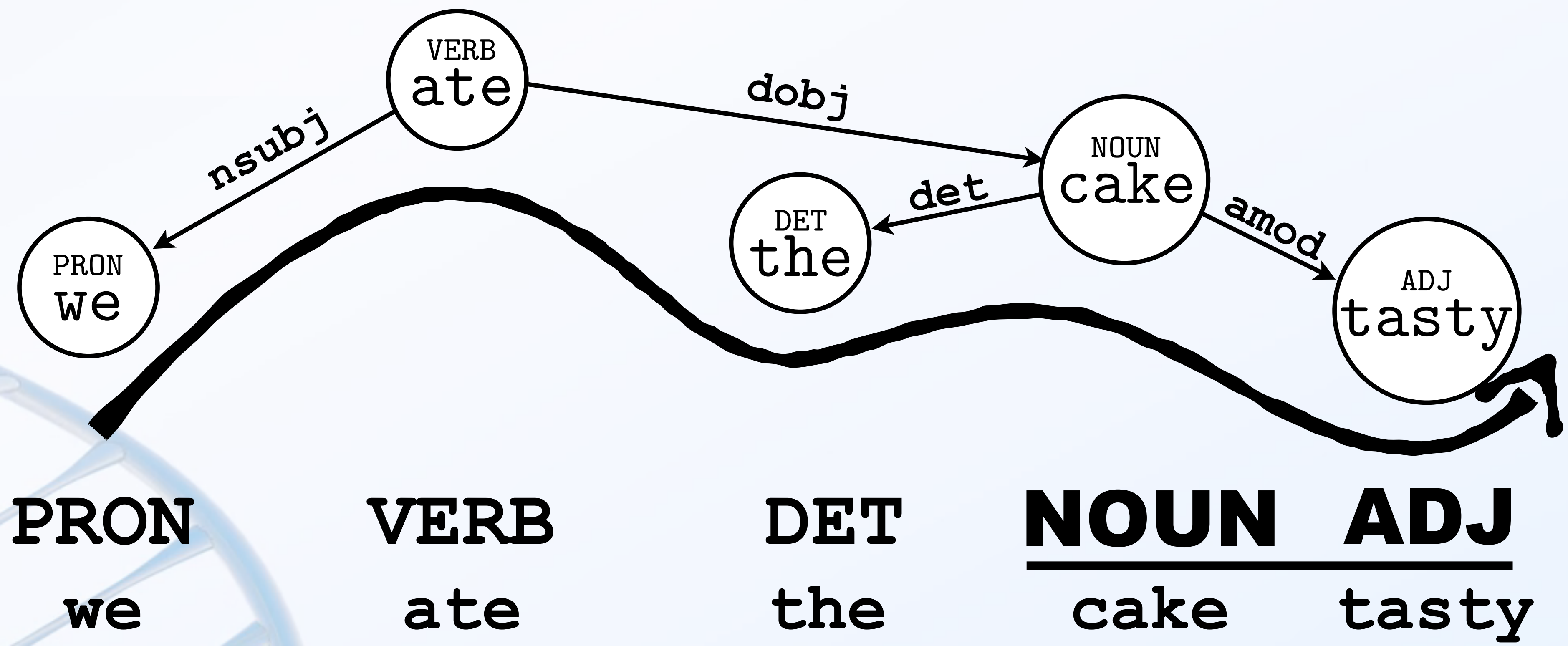
Surface Realization



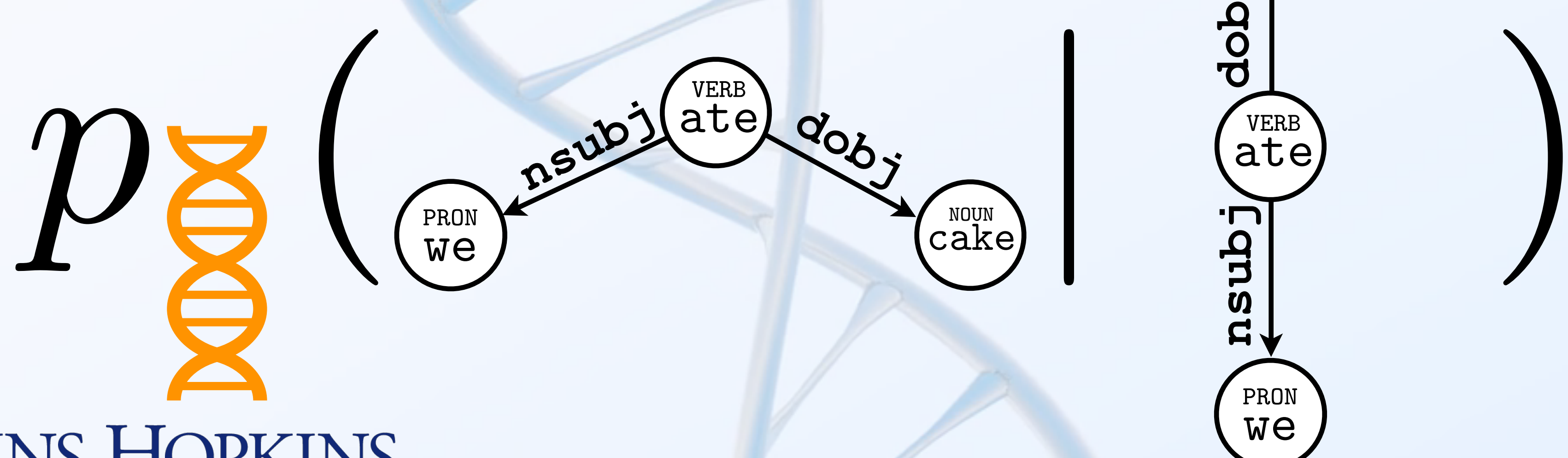
Loglinear model



Surface Realization



Loglinear model



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How to find ?

Source

Target

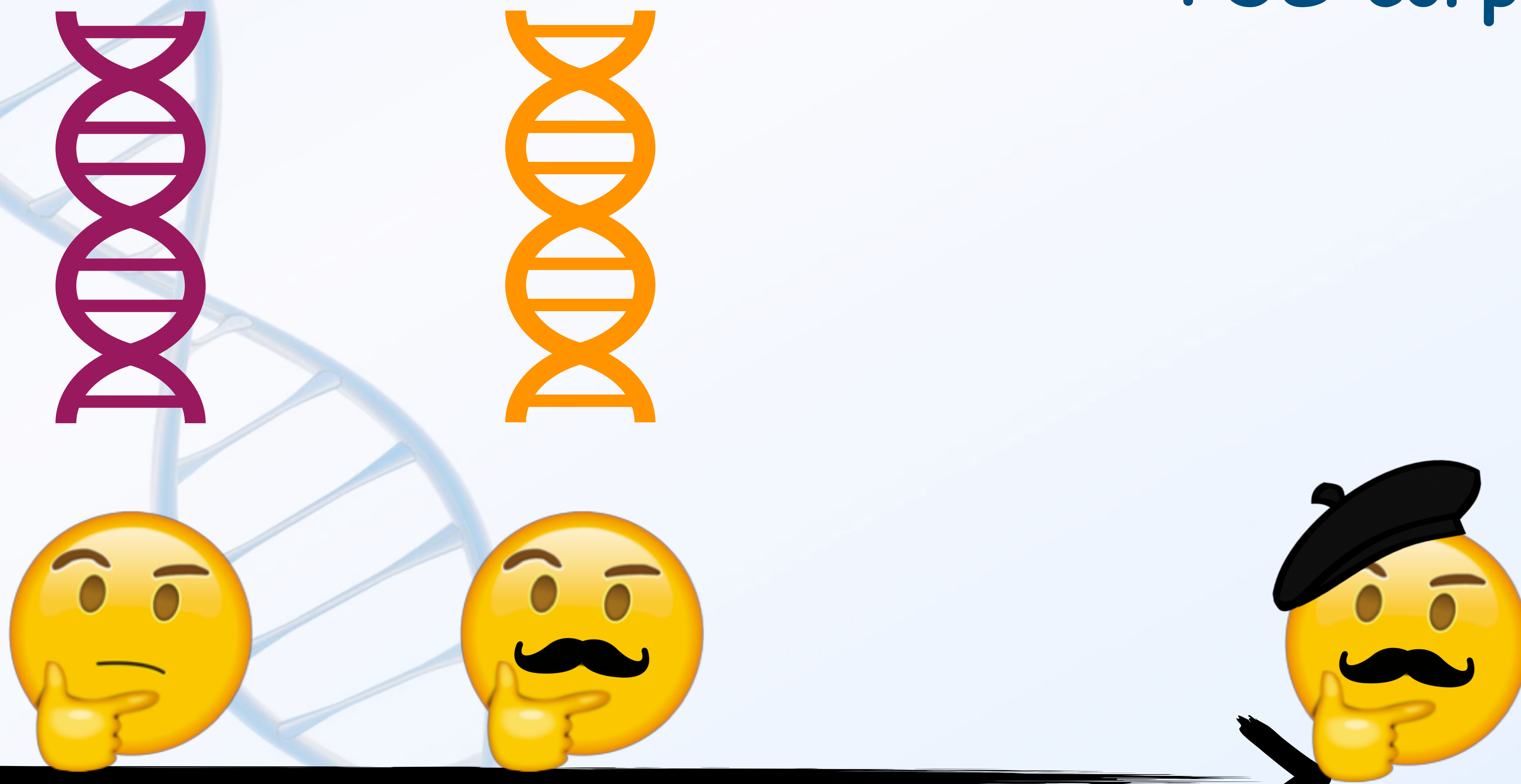
POS corpus

How to find ?

Source

Source'

Target
POS corpus



Surface similarity

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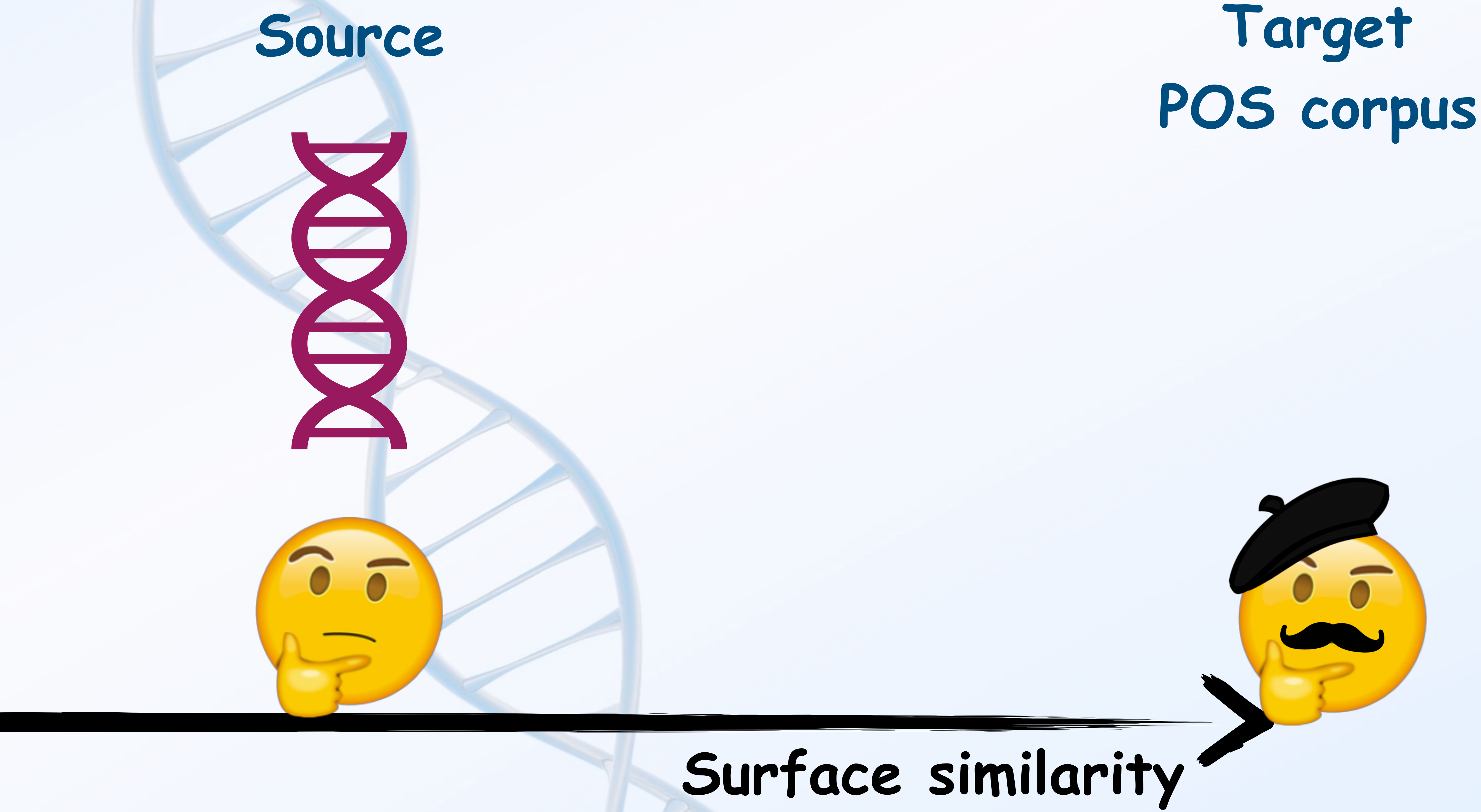
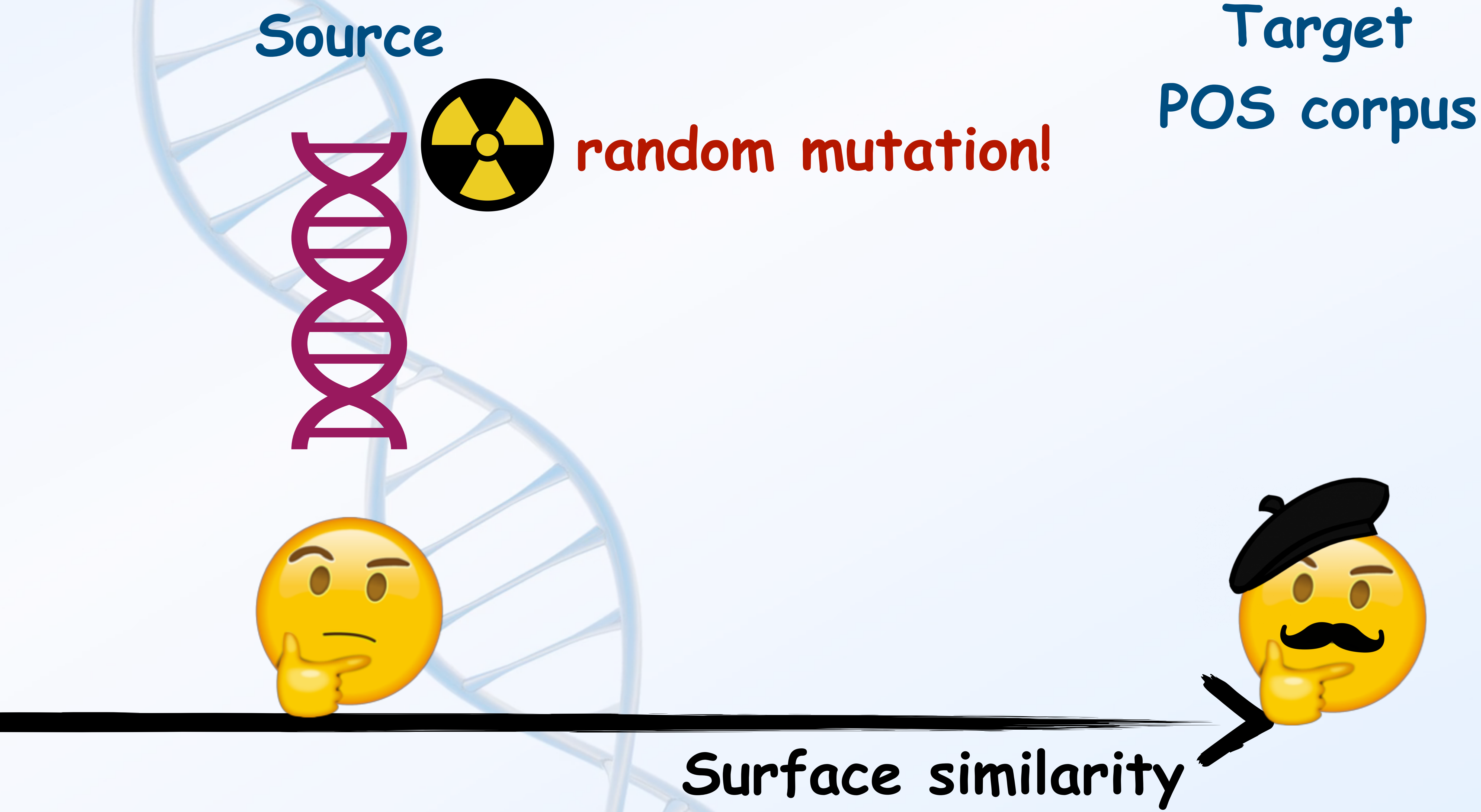
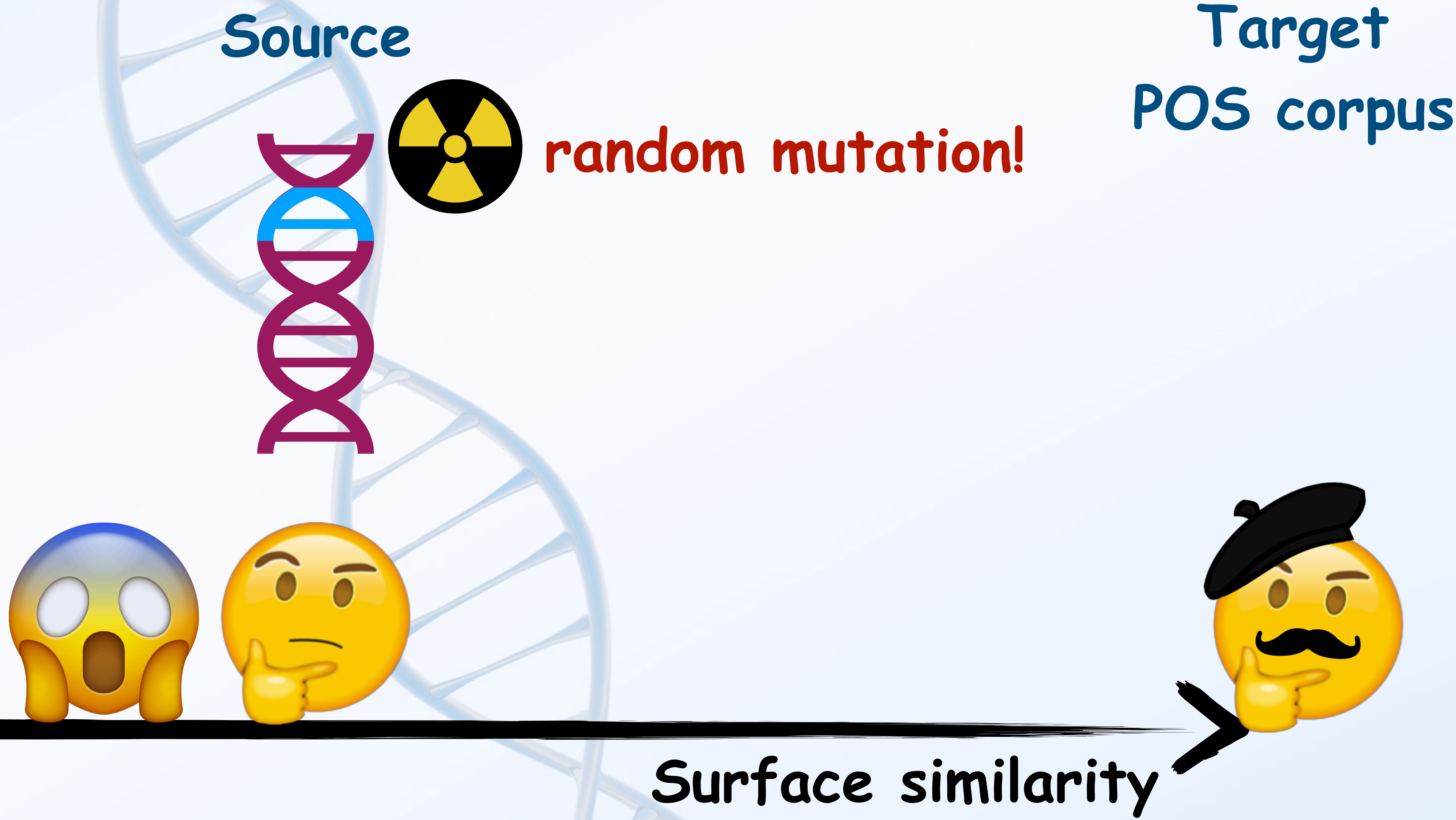
Scattershot



Scattershot



Scattershot



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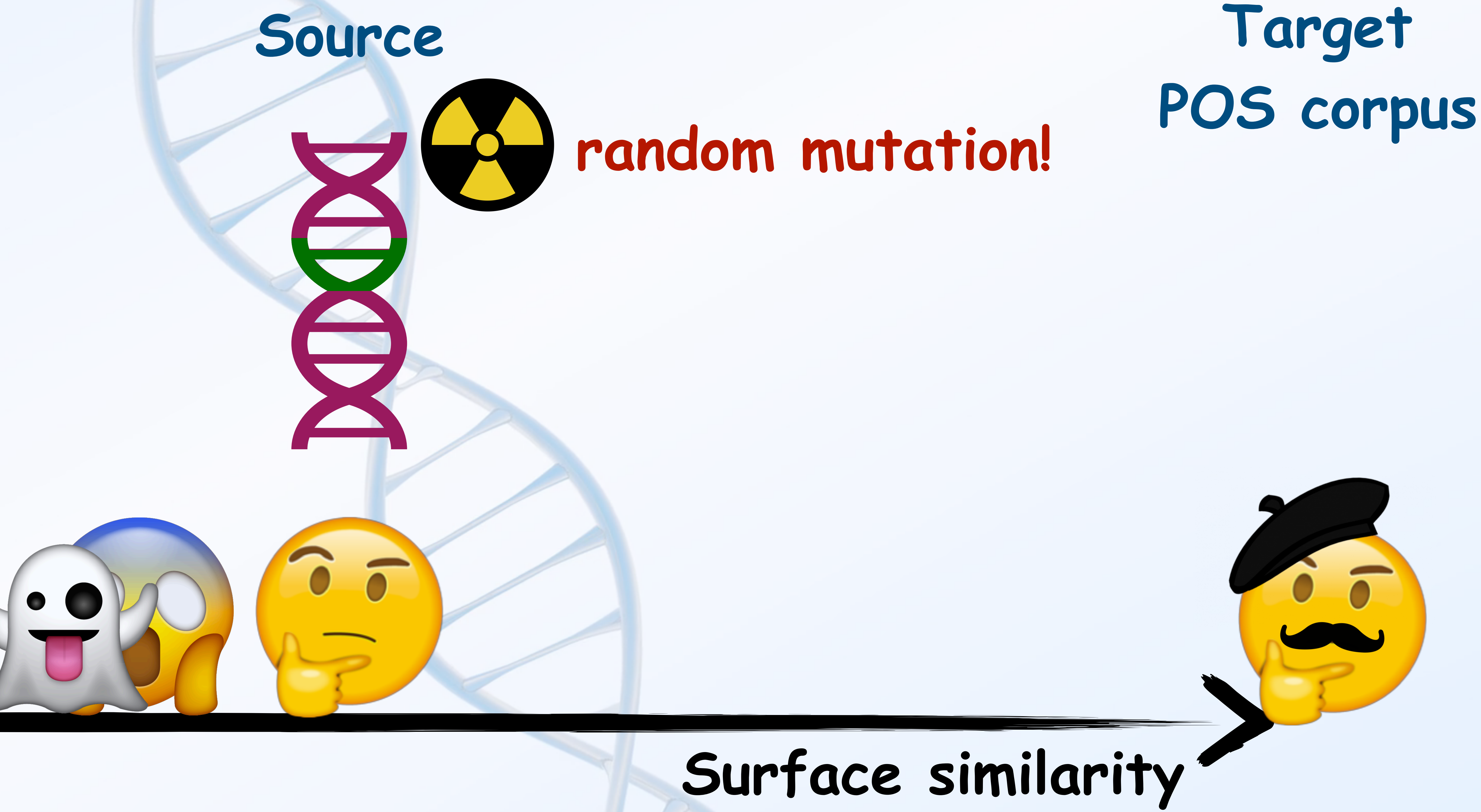
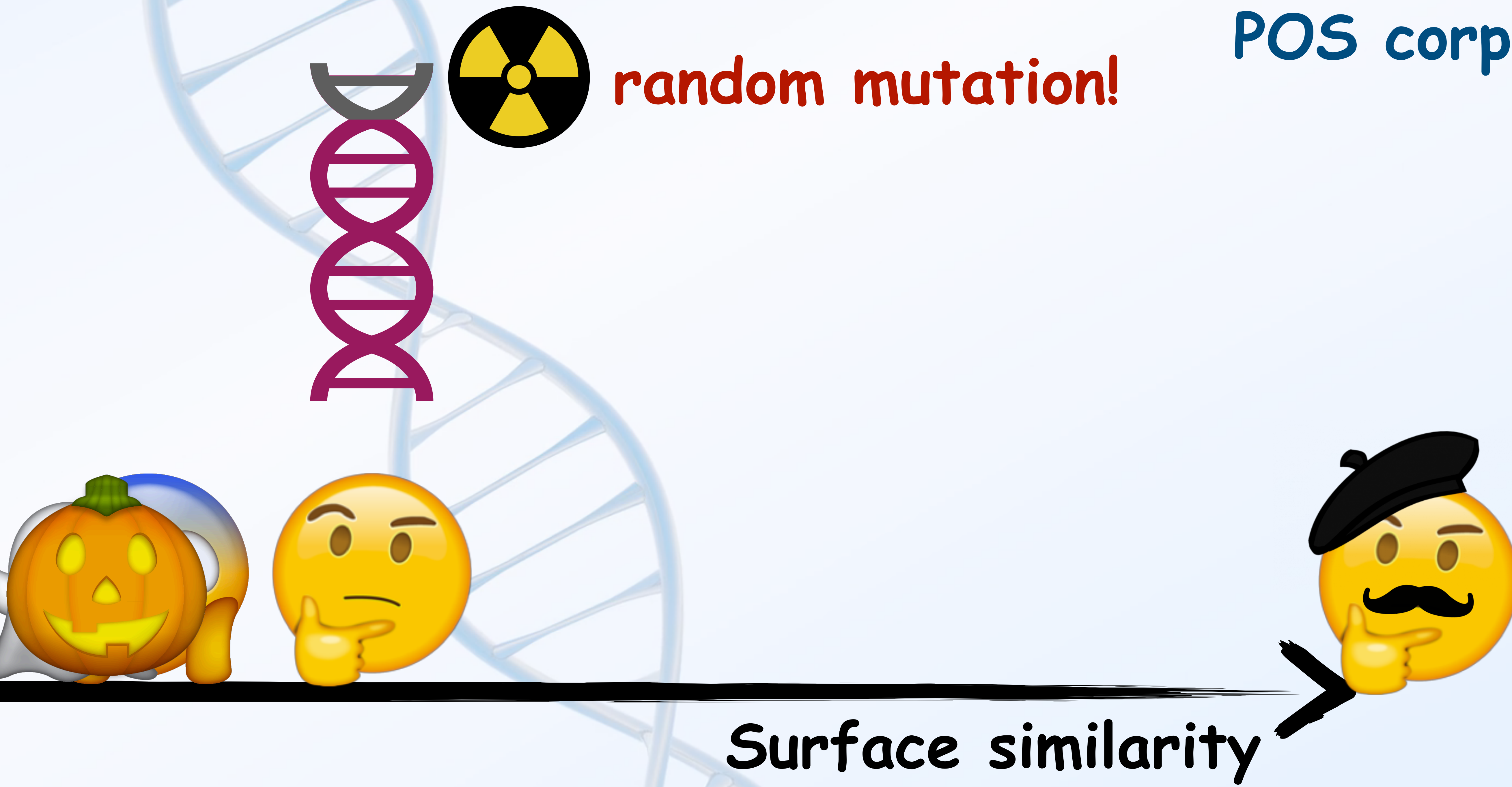


Scattershot

Source

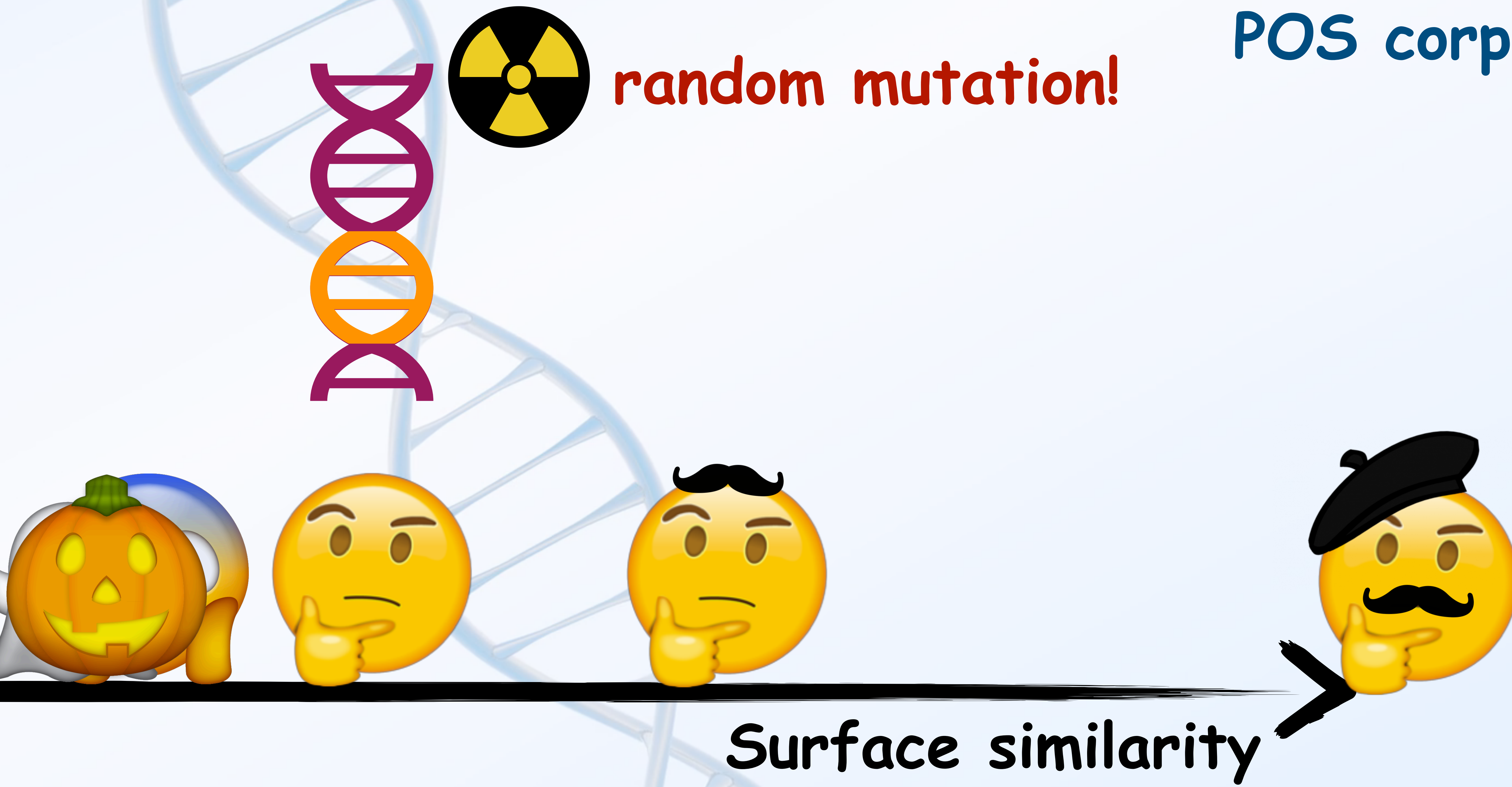
Target
POS corpus



Scattershot

Source

Target
POS corpus



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UNIVERSITY

This Paper: “Intelligent Design”

Source

Target

POS corpus

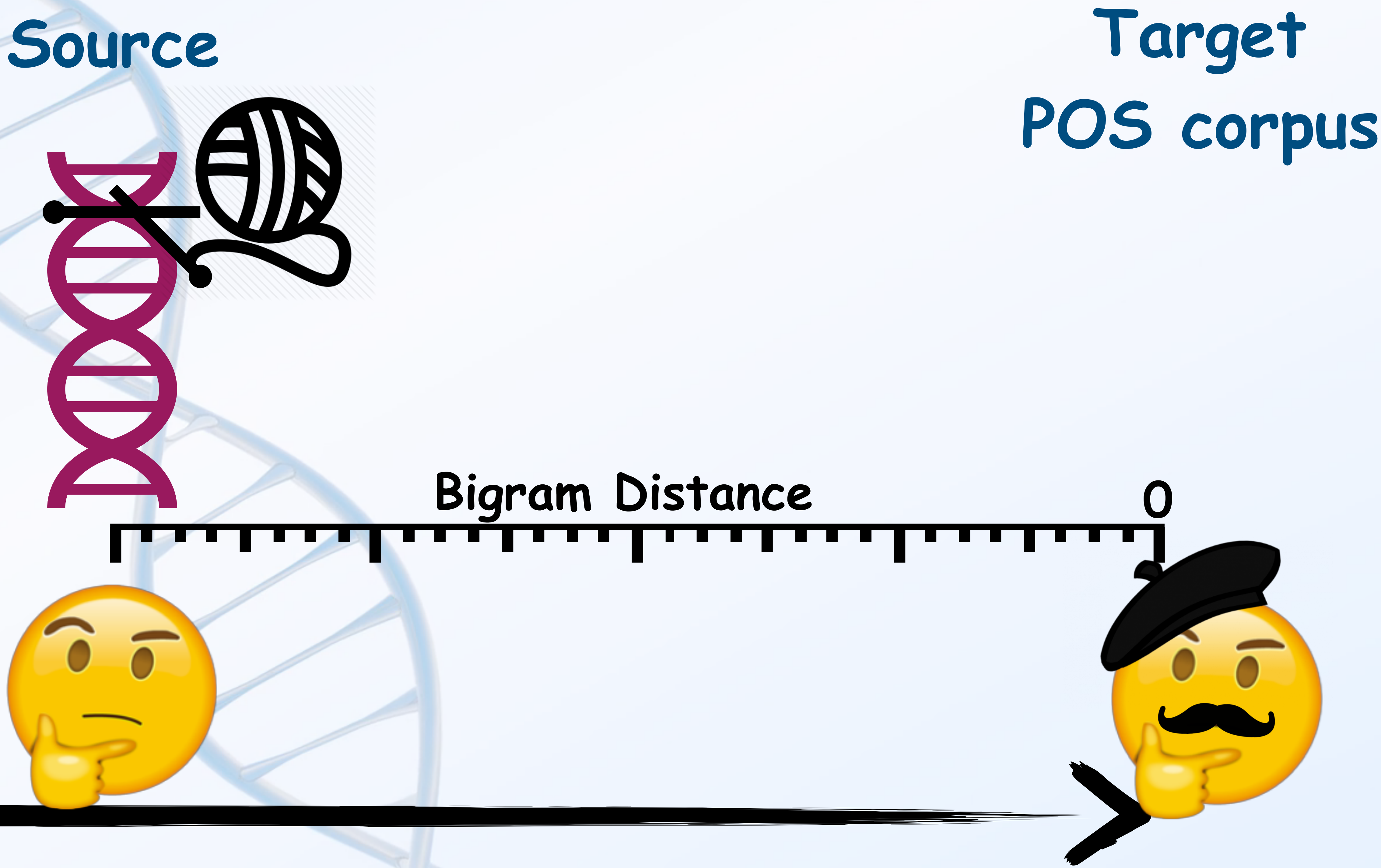
This Paper: “Intelligent Design”

Source

Target

POS corpus

This Paper: “Intelligent Design”



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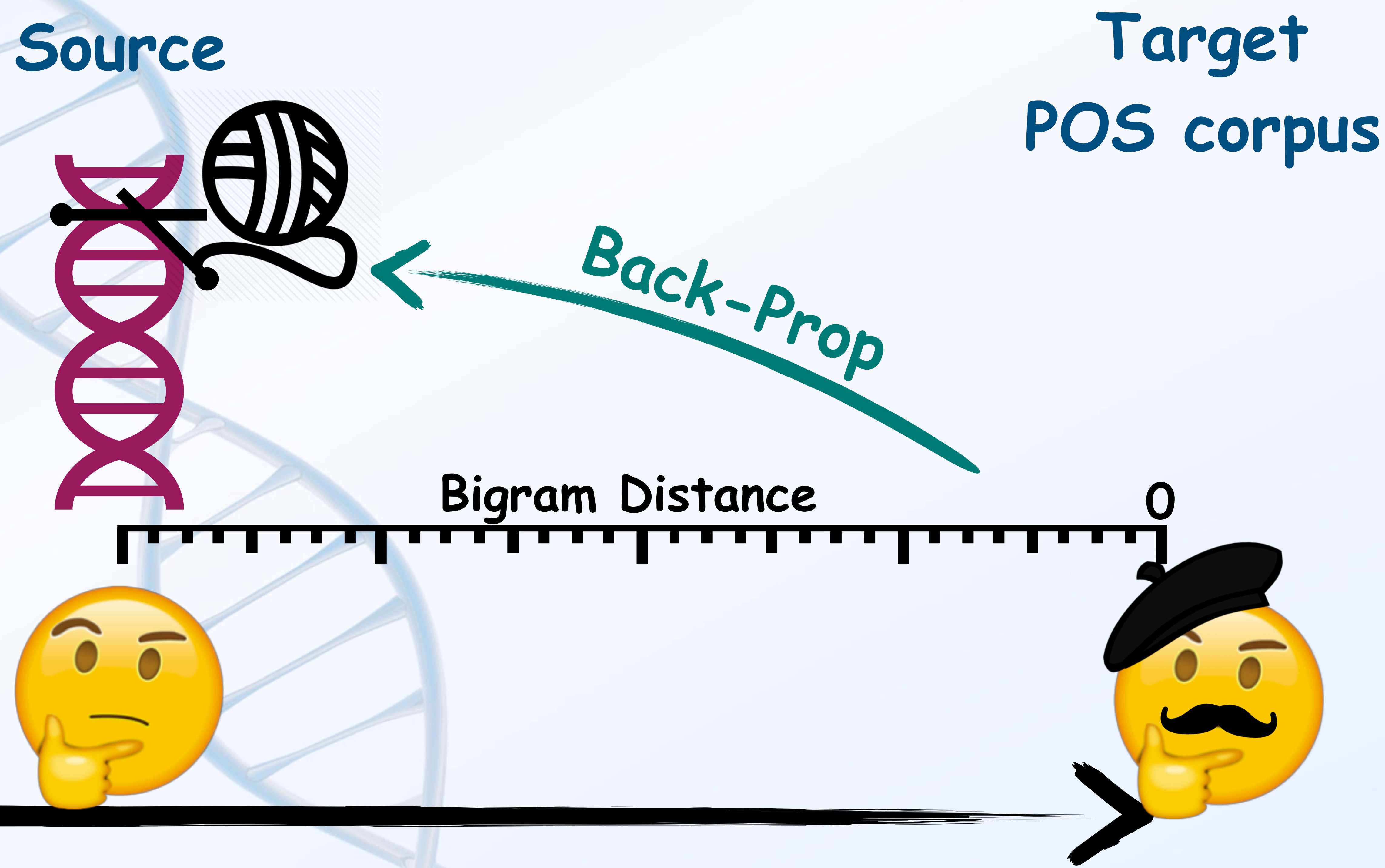

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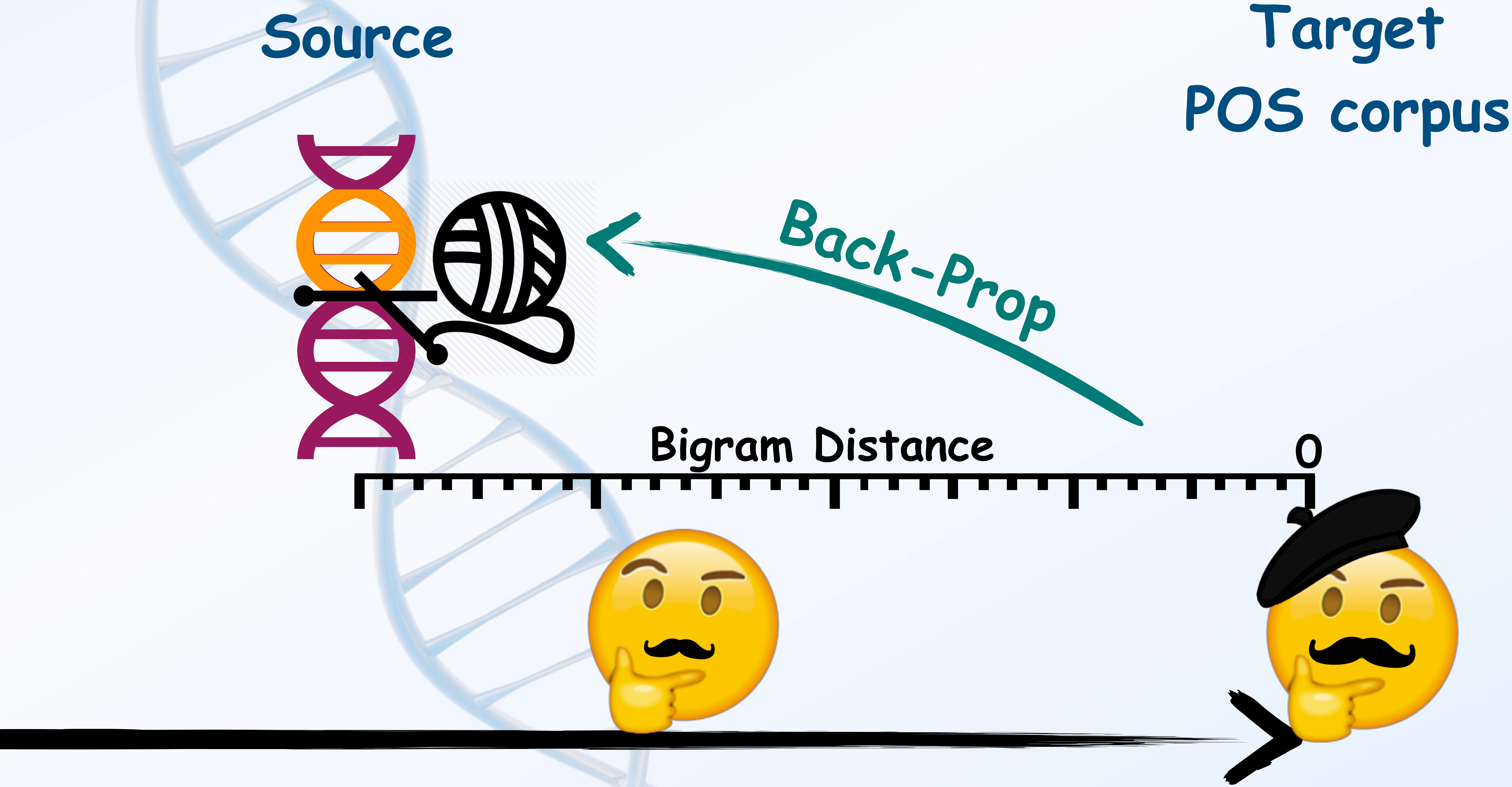

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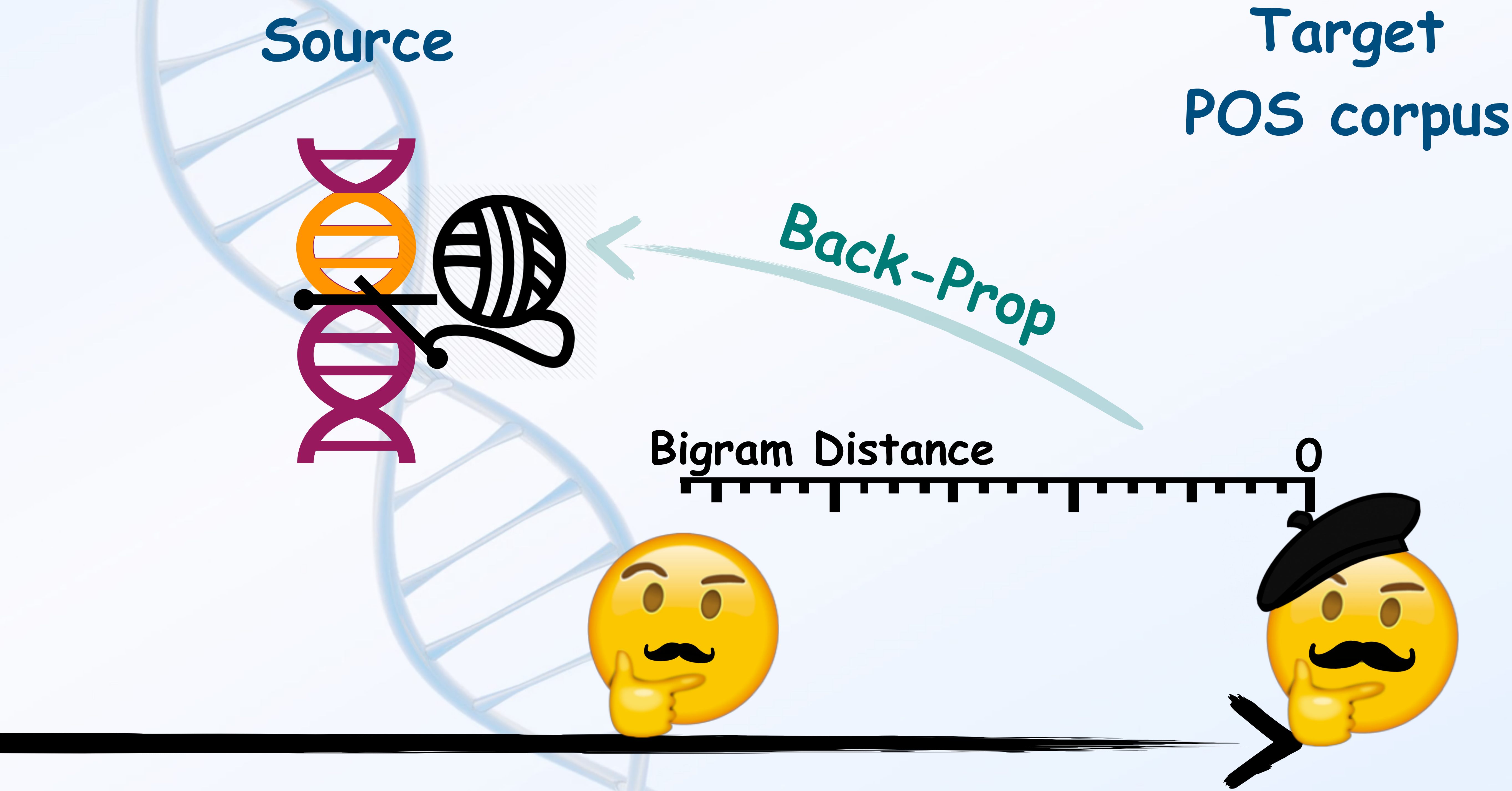
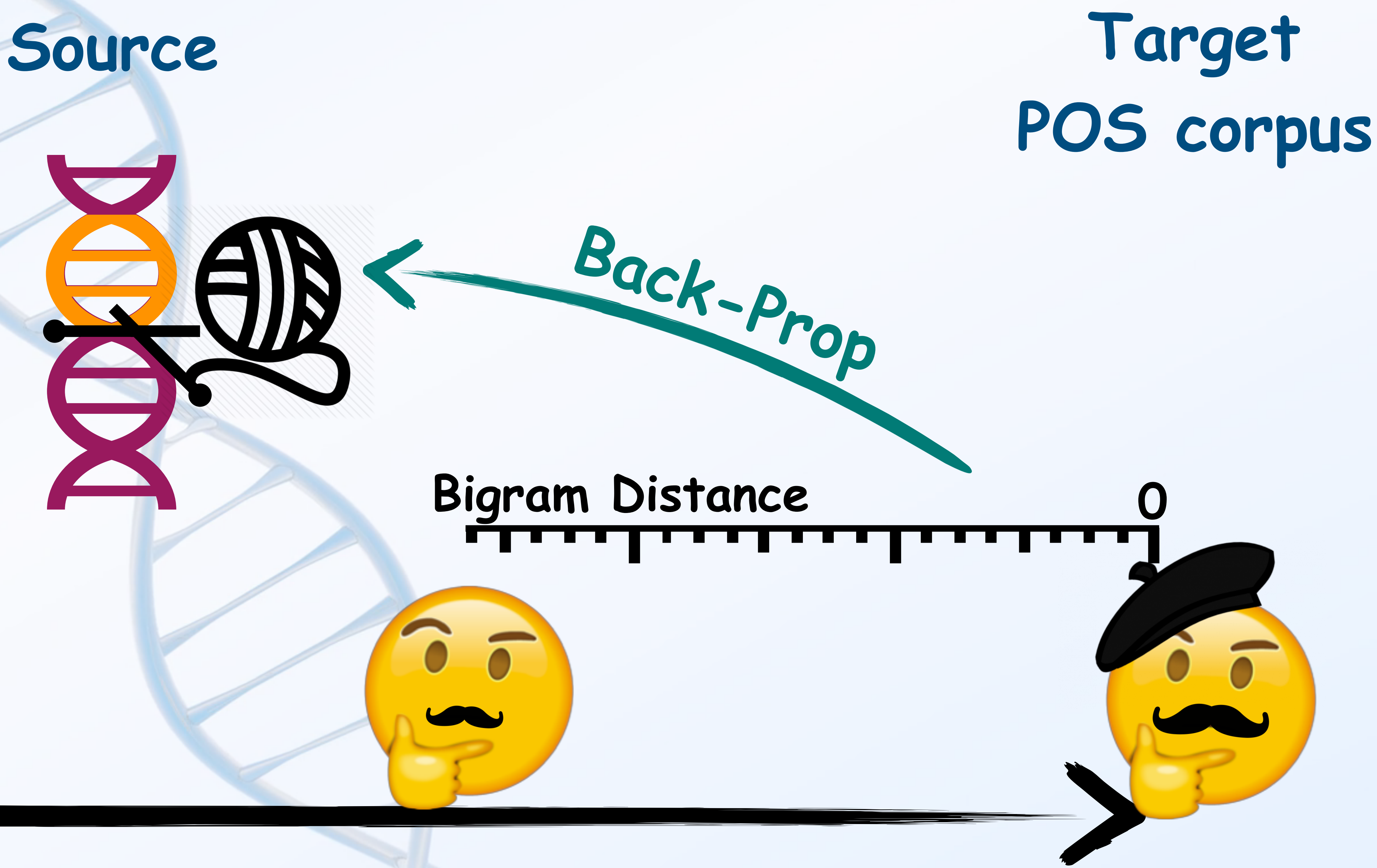


Johns Hopkins University

This Paper: “Intelligent Design”



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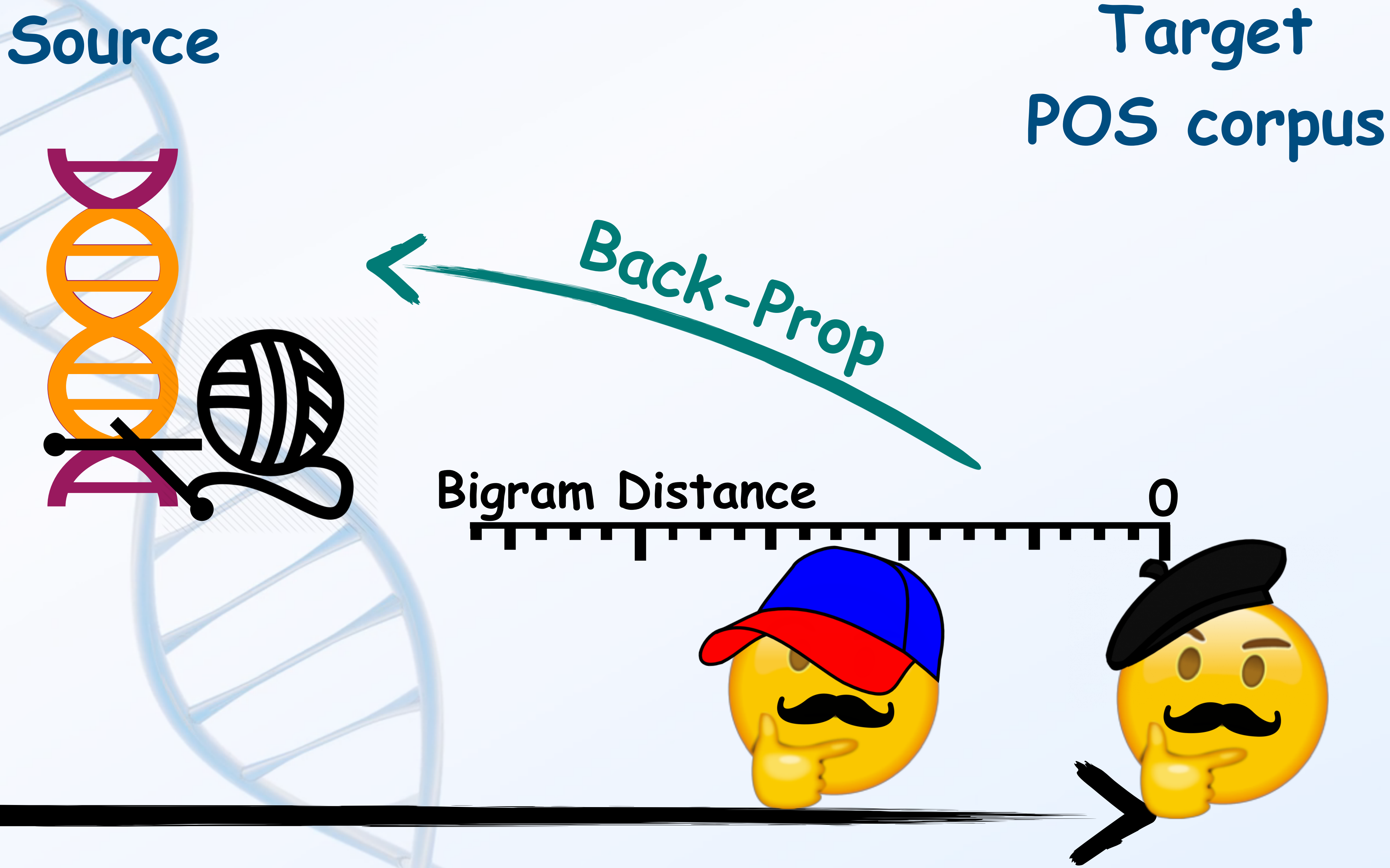


Bigram Distance

Bigram Distance

- Whether the realized surface sentences have the similar POS-bigrams to the target language

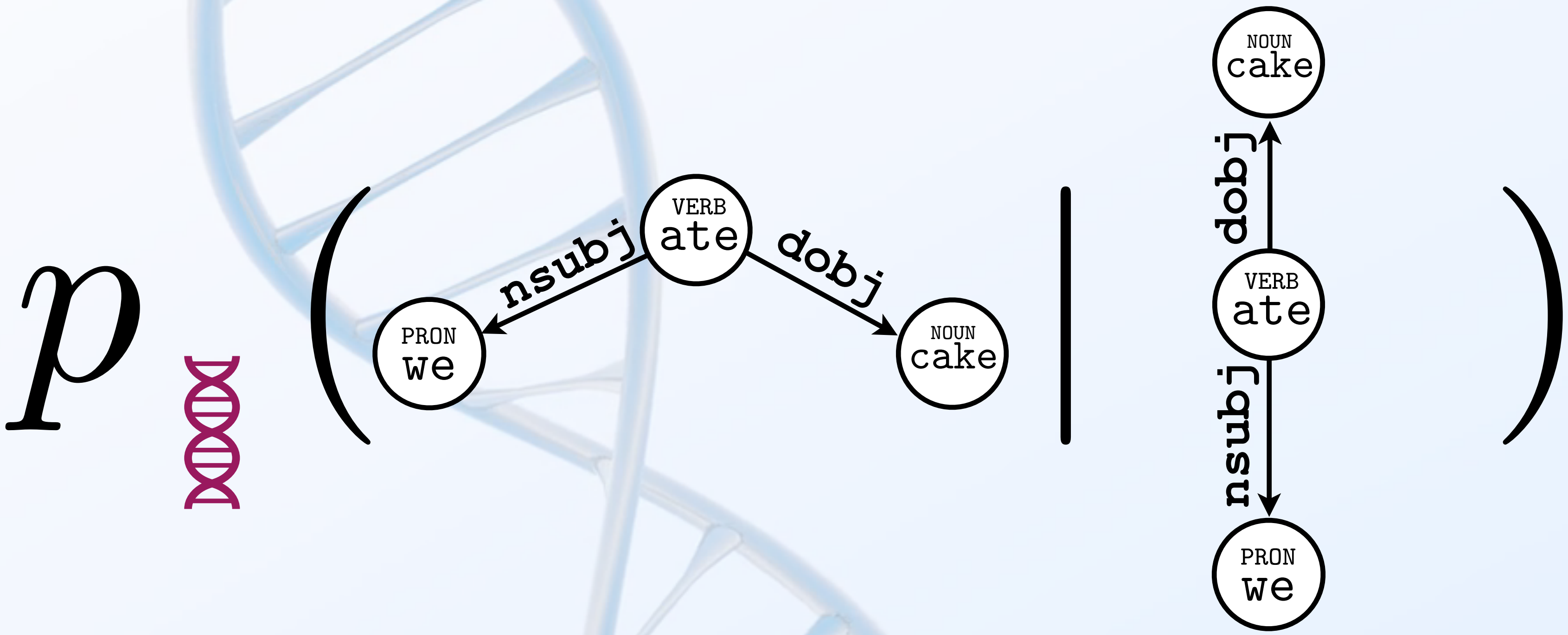
Bigram Distance

- Whether the realized surface sentences have the similar POS-bigrams to the target language
- How to compute the POS-bigrams counts?

Bigram Distance

- Whether the realized surface sentences have the similar POS-bigrams to the target language

- How to compute the POS-bigrams counts?
  - **Expected Counts** from !



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Computing the Expected Counts

by Dynamic Programming

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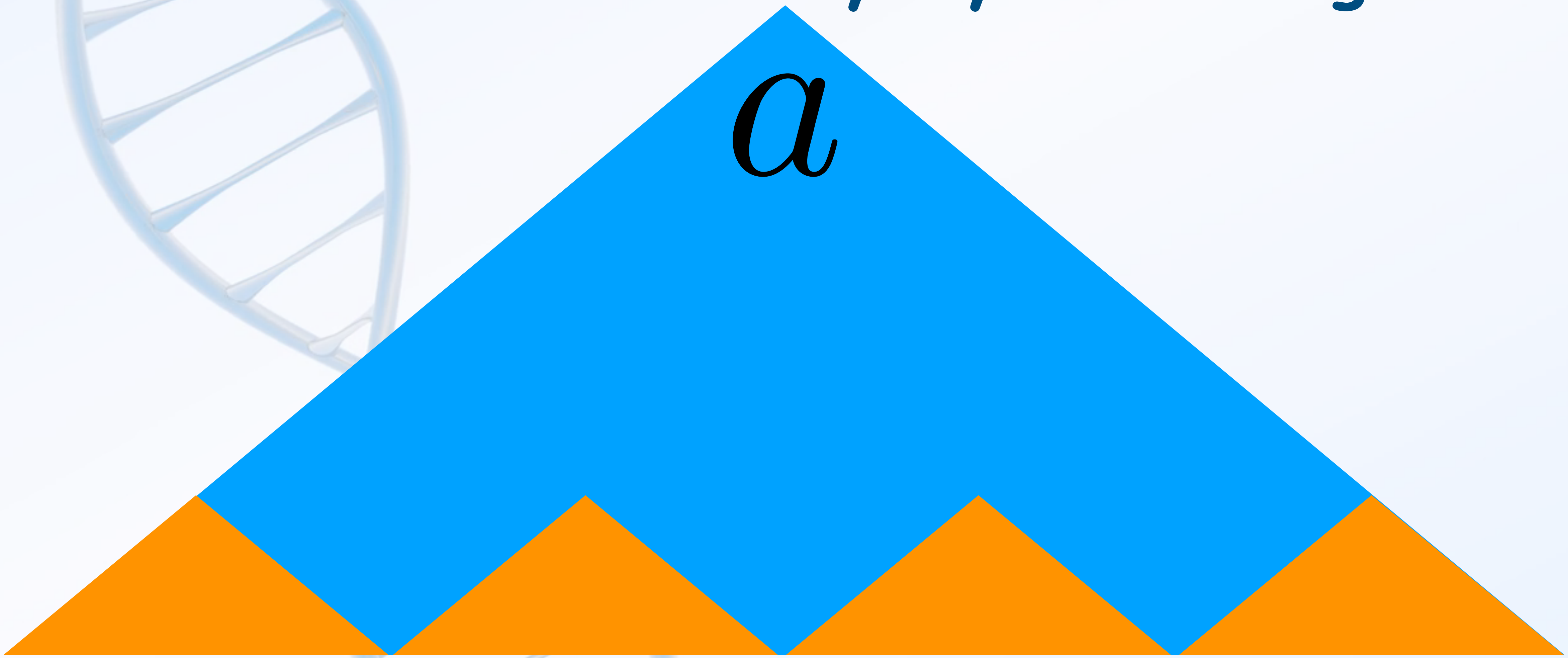
Computing the Expected Counts

by Dynamic Programming



Computing the Expected Counts

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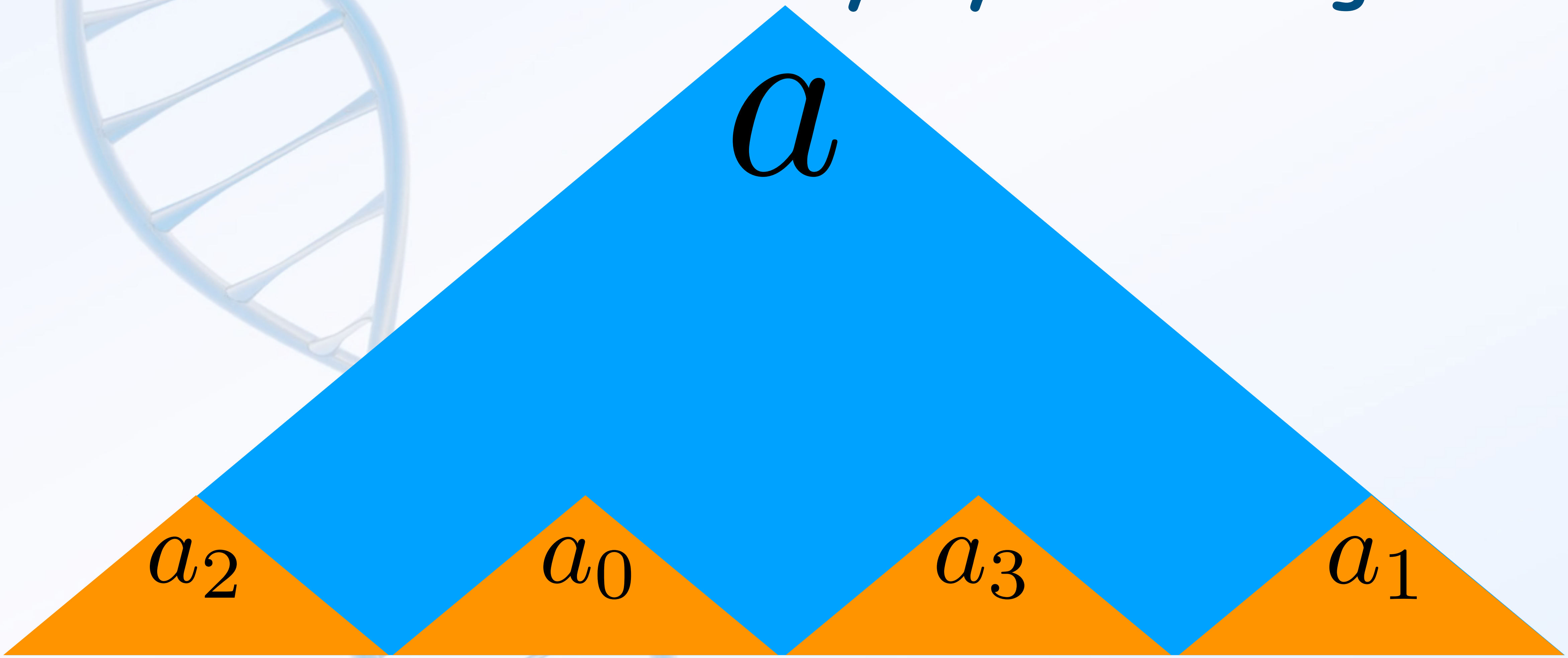
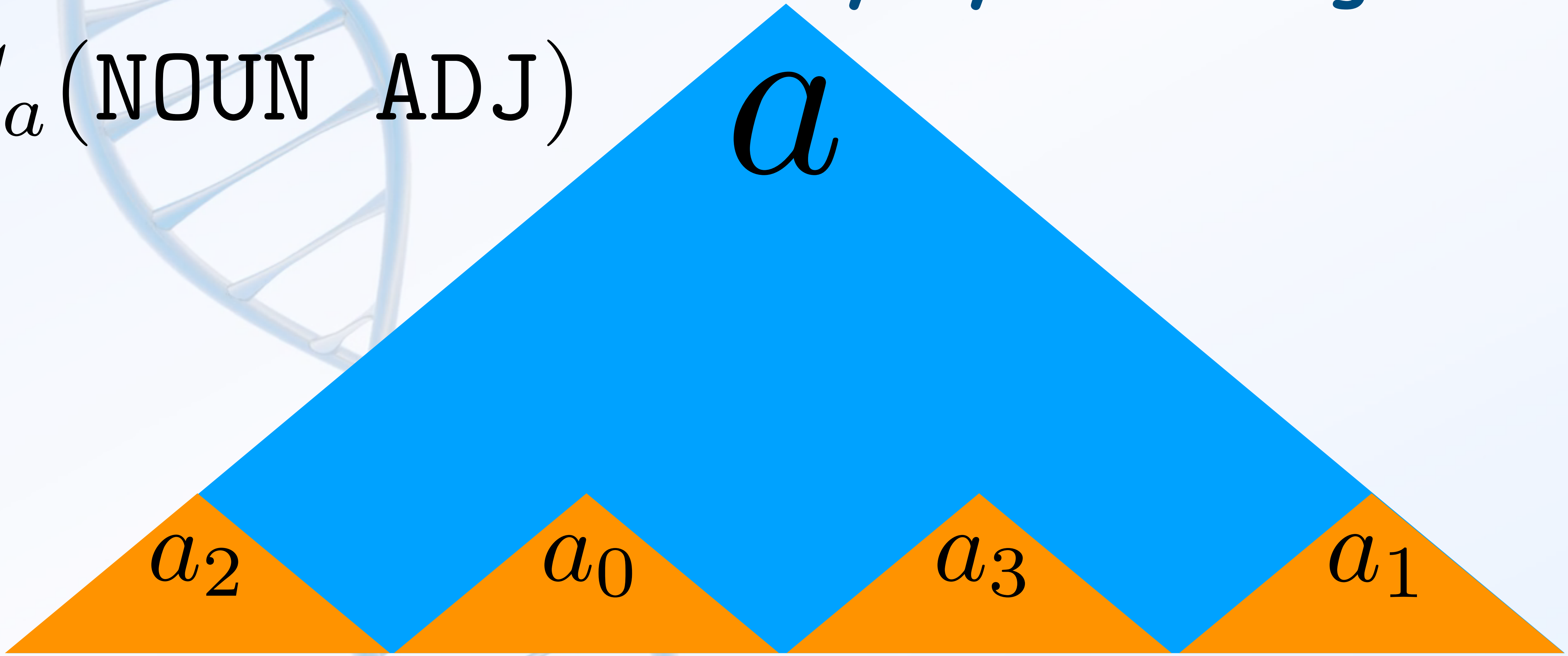


Computing the Expected Counts

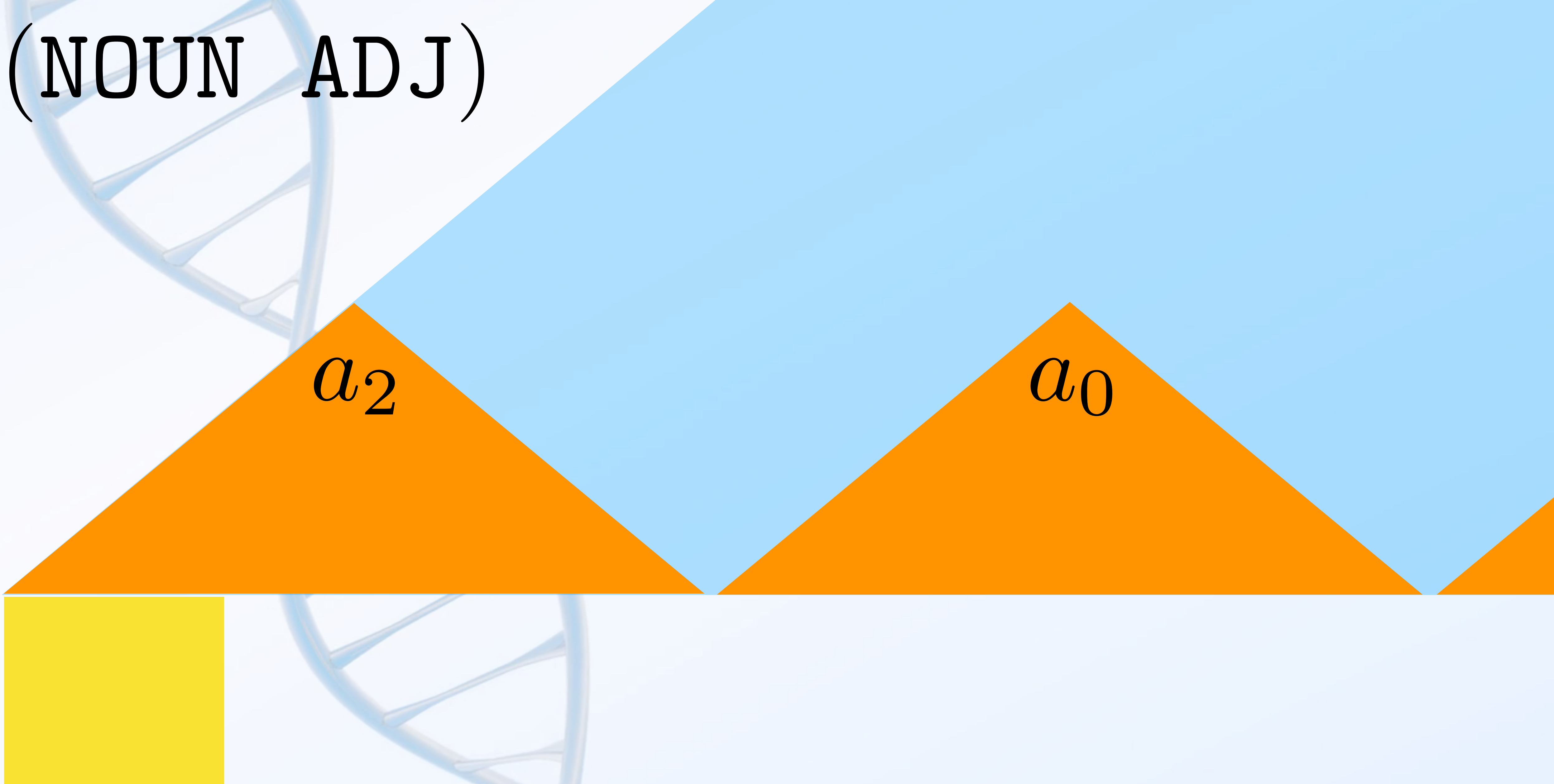
by Dynamic Programming

$C_a(\texttt{NOUN ADJ})$



Computing the Expected Counts
by Dynamic Programming

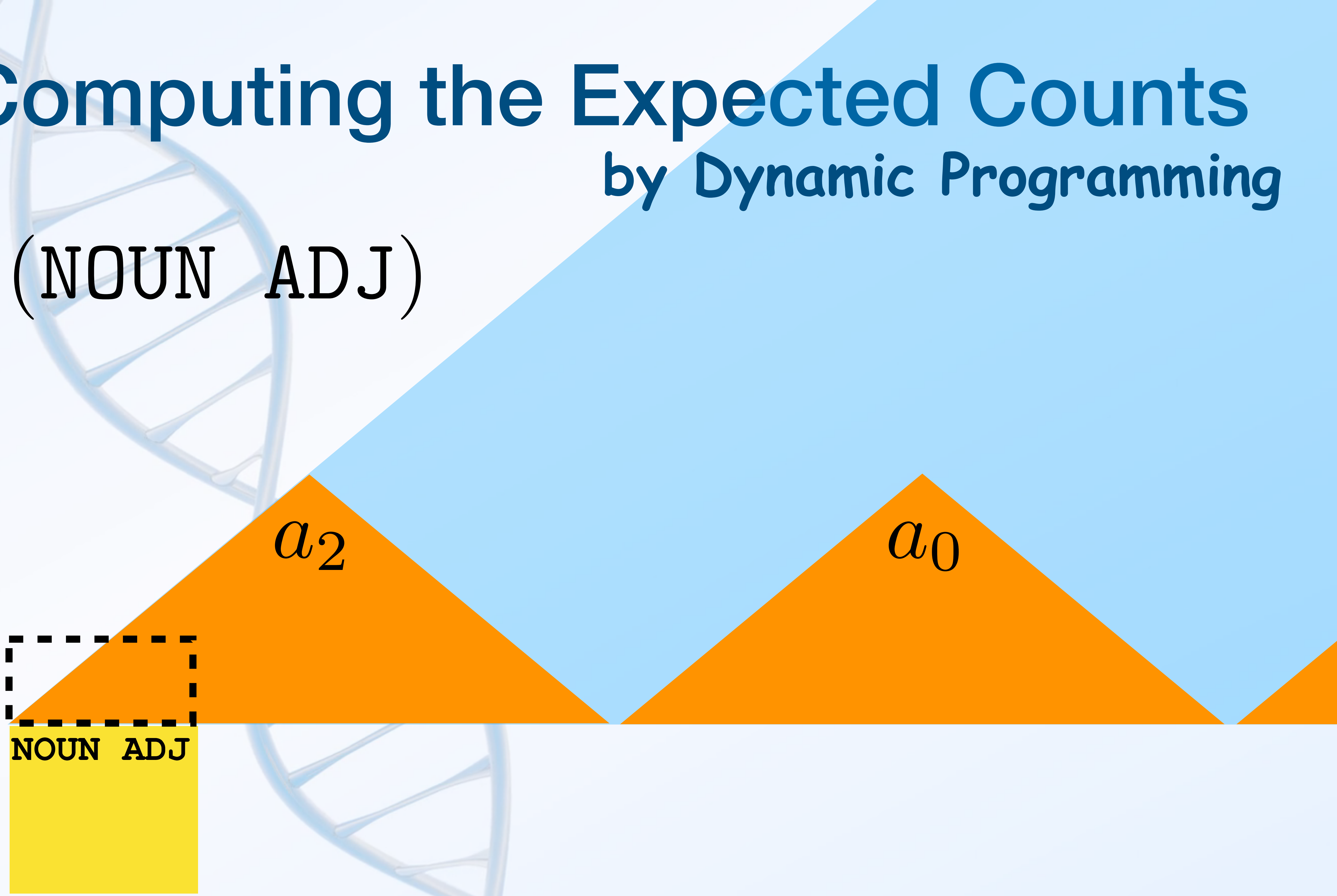
$C_a(\texttt{NOUN ADJ})$



Computing the Expected Counts

by Dynamic Programming

$C_a(\texttt{NOUN ADJ})$



Computing the Expected Counts
by Dynamic Programming

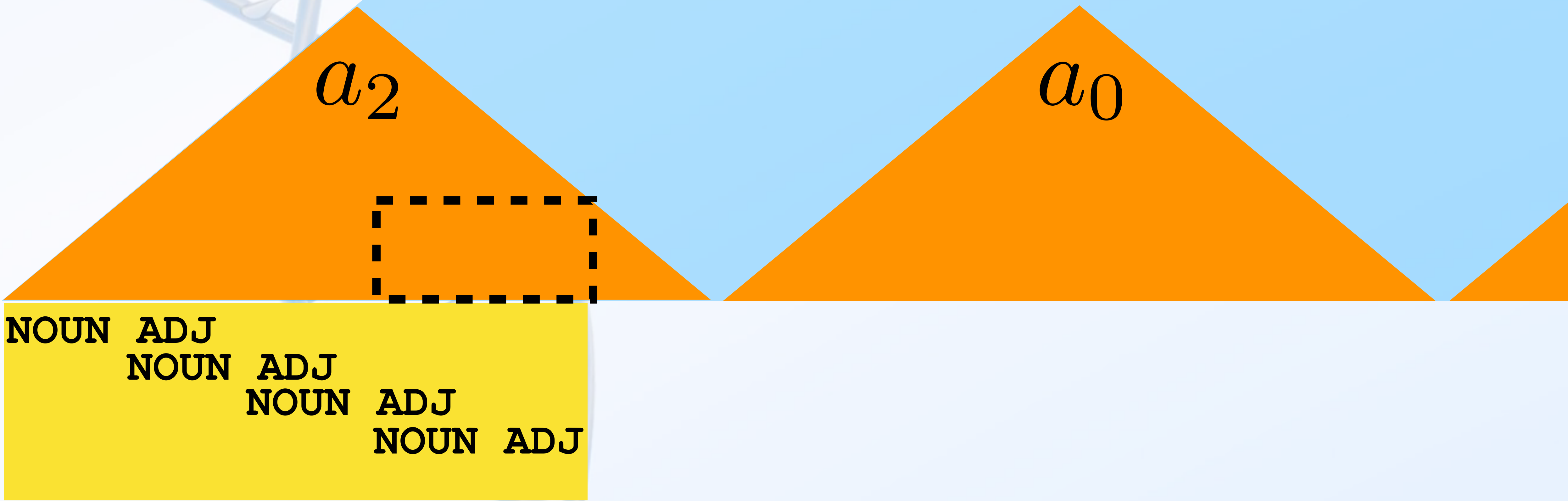
$C_a(\texttt{NOUN ADJ})$

Computing the Expected Counts
by Dynamic Programming

$$C_a(\texttt{NOUN ADJ})$$

Computing the Expected Counts
by Dynamic Programming

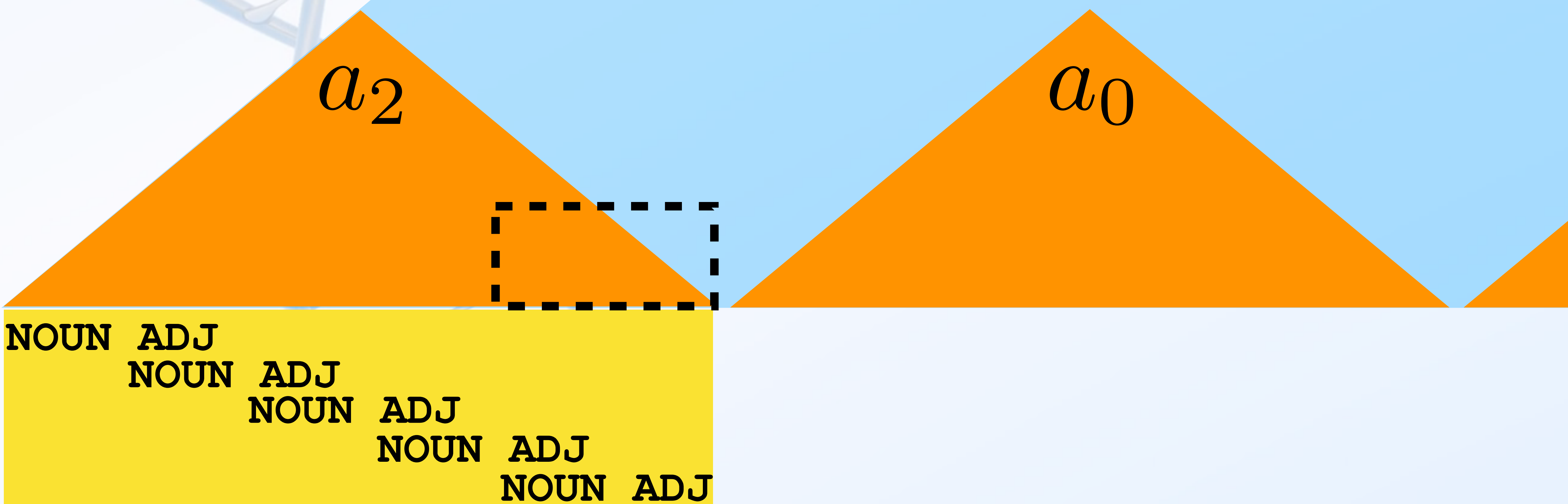
$$C_a(\texttt{NOUN ADJ})$$



Computing the Expected Counts

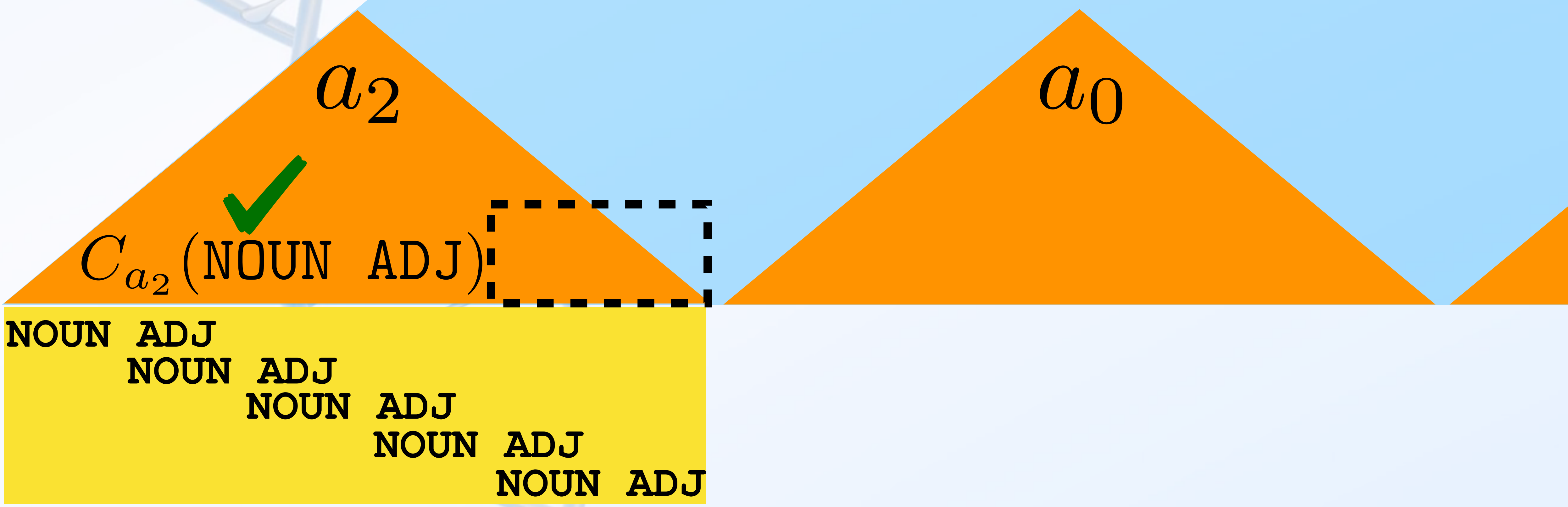
by Dynamic Programming

$$C_a(\texttt{NOUN ADJ})$$



Computing the Expected Counts
by Dynamic Programming

$$C_a(\mathtt{NOUN\ \ ADJ})$$



Computing the Expected Counts

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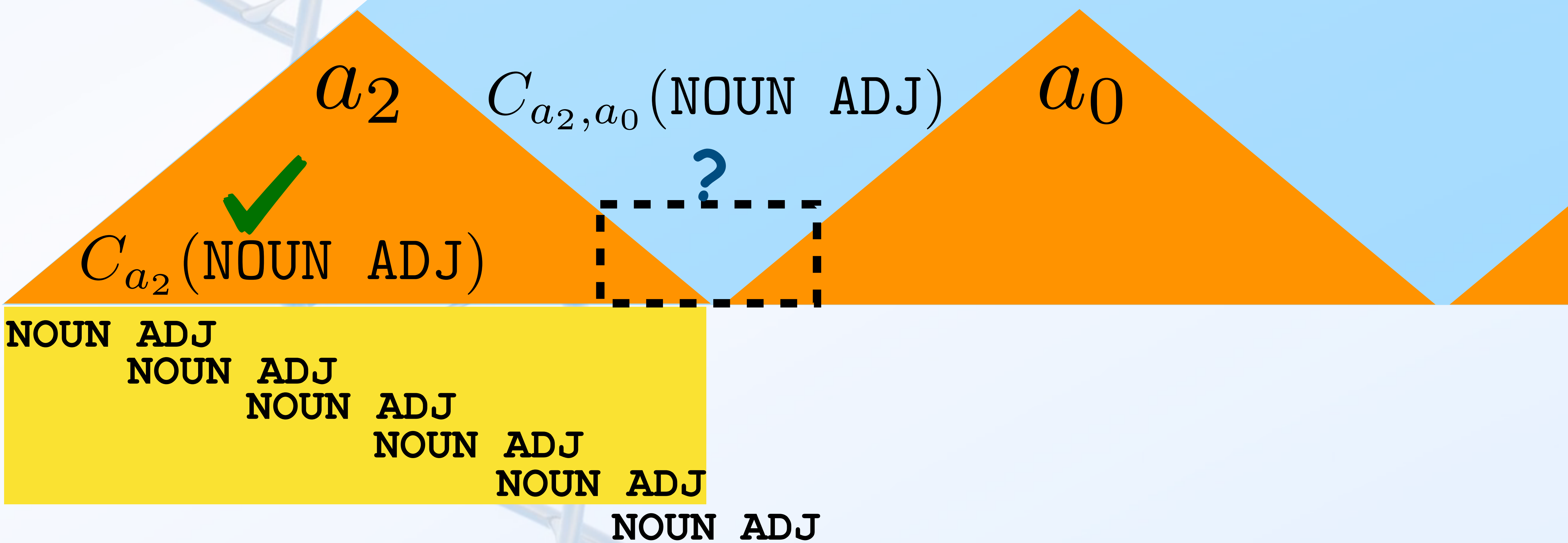
$$C_a(\texttt{NOUN ADJ})$$

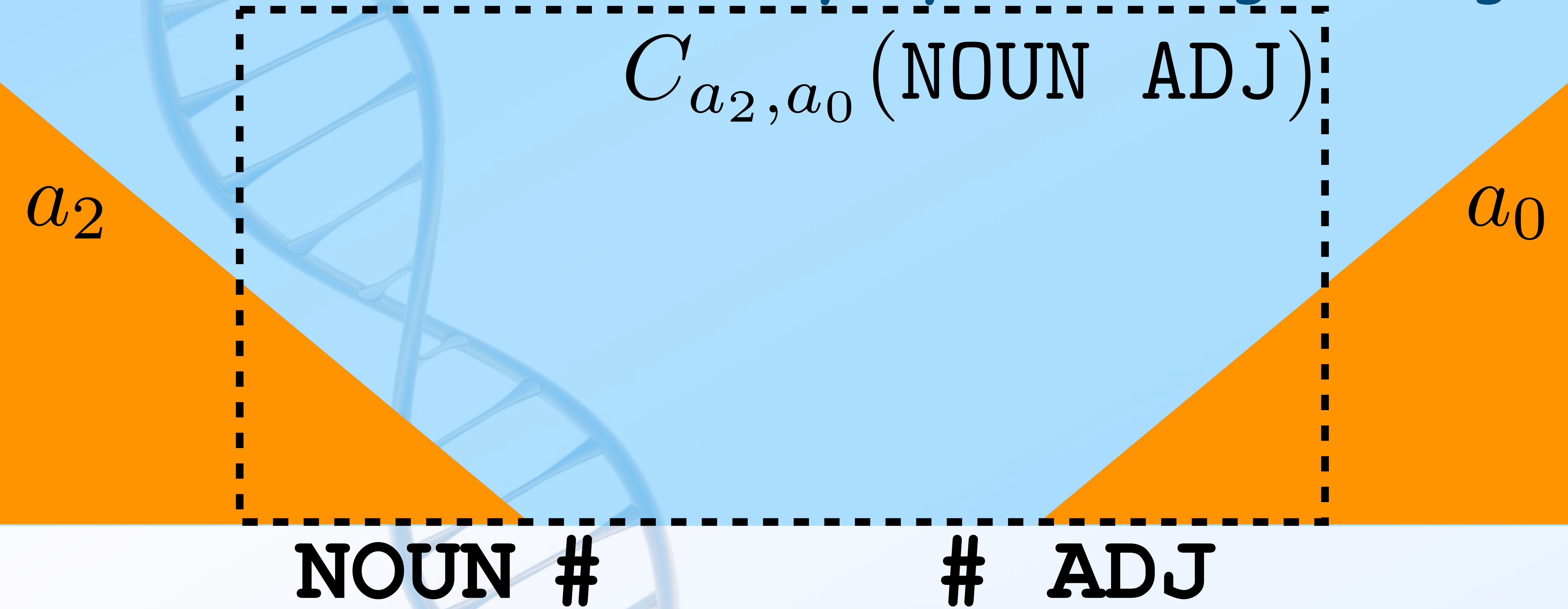


Computing the Expected Counts

by Dynamic Programming

NOUN ADJ

Computing the Expected Counts
by Dynamic Programming



Computing the Expected Counts

by Dynamic Programming

$$C_{a_2,a_0}(\texttt{NOUN ADJ})$$

a_2

a_0

NOUN #

 # ADJ

$$C_{a_2}(\texttt{NOUN \#})$$

$$C_{a_0}(\texttt{\# ADJ})$$

Computing the Expected Counts

by Dynamic Programming

$C_{a_2, a_0}(\texttt{NOUN ADJ})$

a_2 a_0

NOUN # **# ADJ**

$C_{a_2}(\texttt{NOUN \#})$ ✔ $C_{a_0}(\texttt{\# ADJ})$ ✔

Computing the Expected Counts

by Dynamic Programming

$C_{a_2,a_0}(\texttt{NOUN ADJ})$

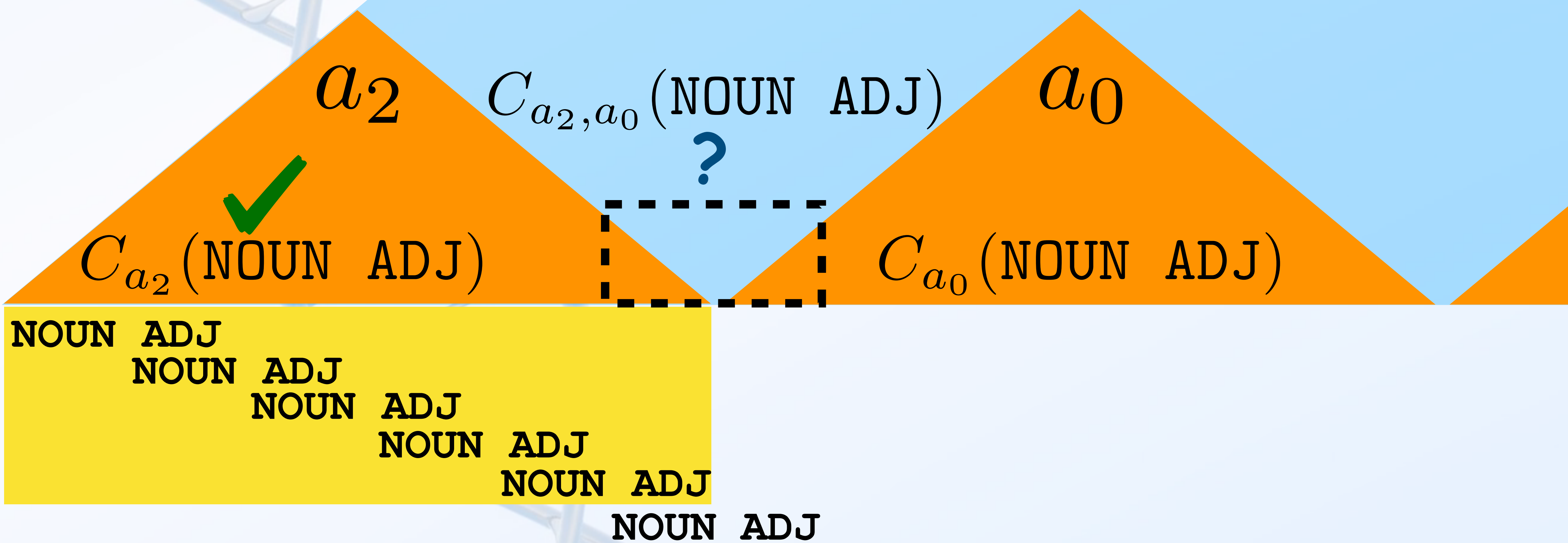
a_2 a_0

NOUN # **# ADJ**

$$C_{a_2}(\texttt{NOUN \#}) \times C_{a_0}(\texttt{\# ADJ})$$

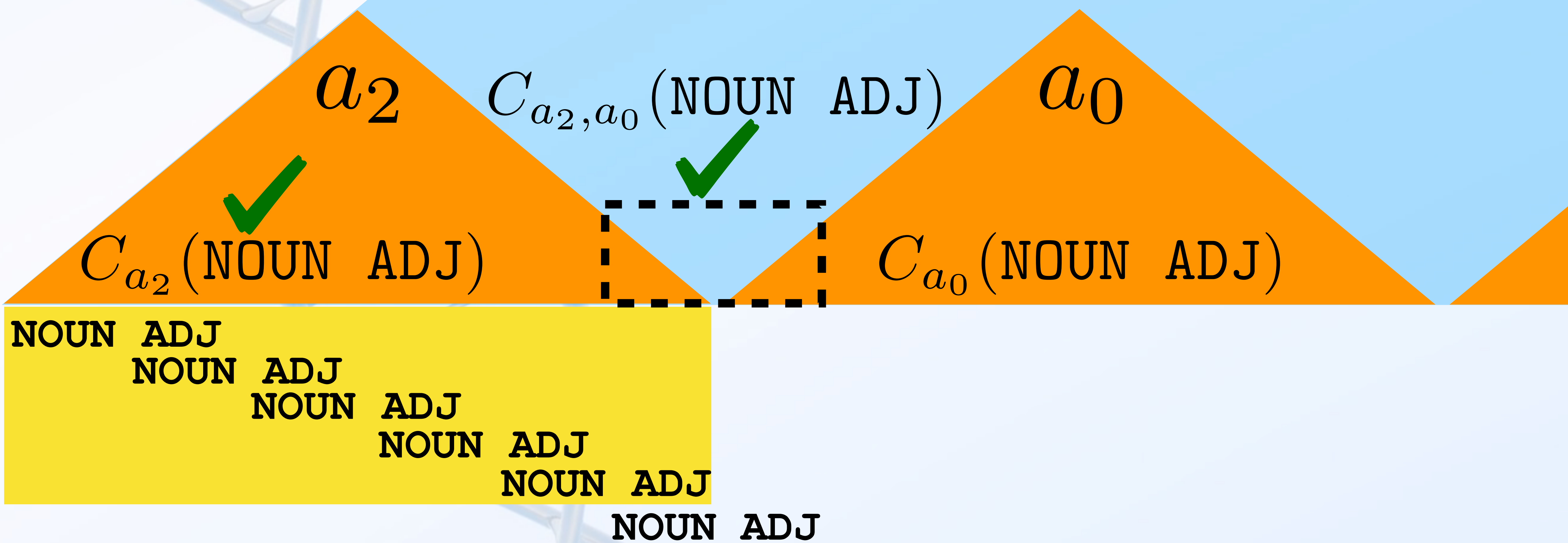
Computing the Expected Counts
by Dynamic Programming

$$C_a(\texttt{NOUN ADJ})$$



Computing the Expected Counts
by Dynamic Programming

$$C_a(\texttt{NOUN ADJ})$$



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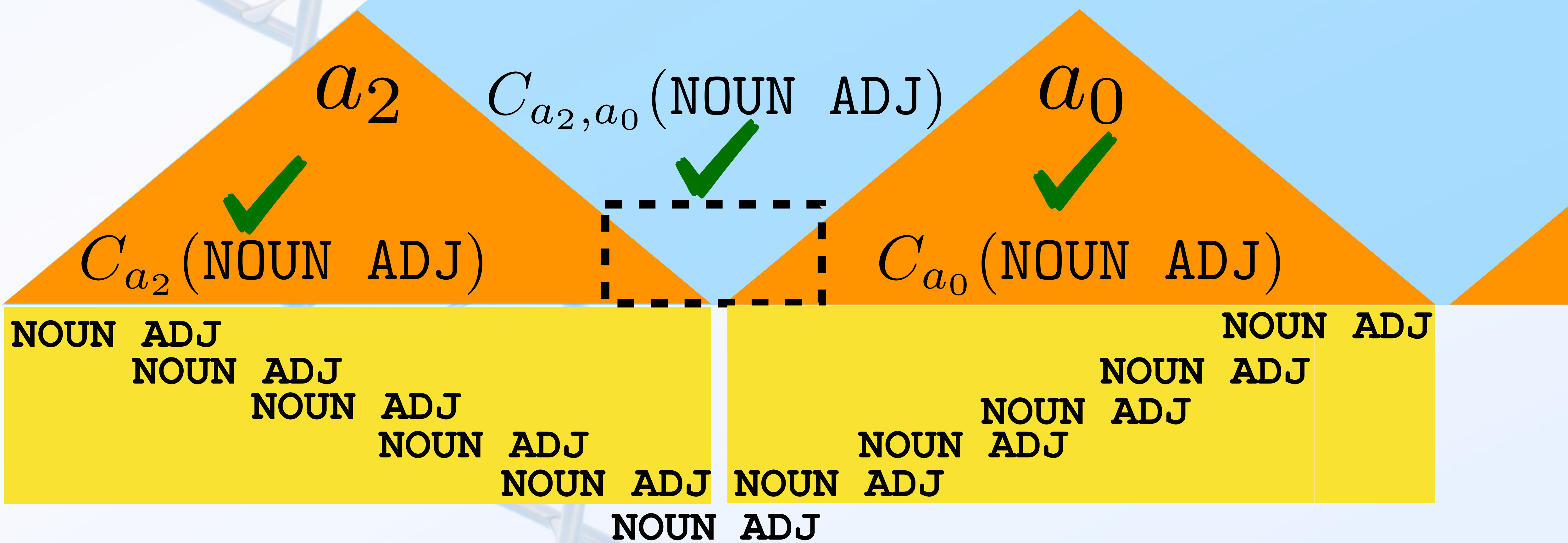
Computing the Expected Counts
by Dynamic Programming

$C_a(\texttt{NOUN ADJ})$



Computing the Expected Counts

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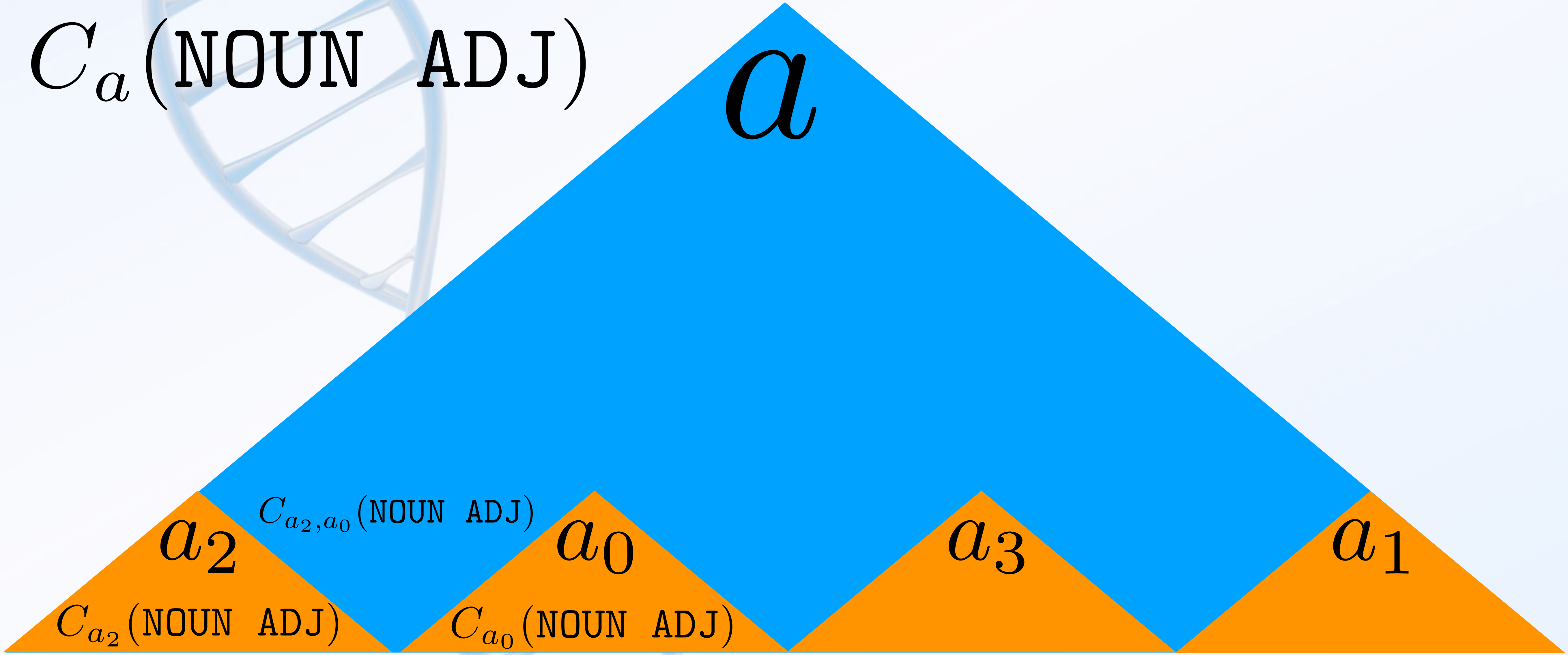

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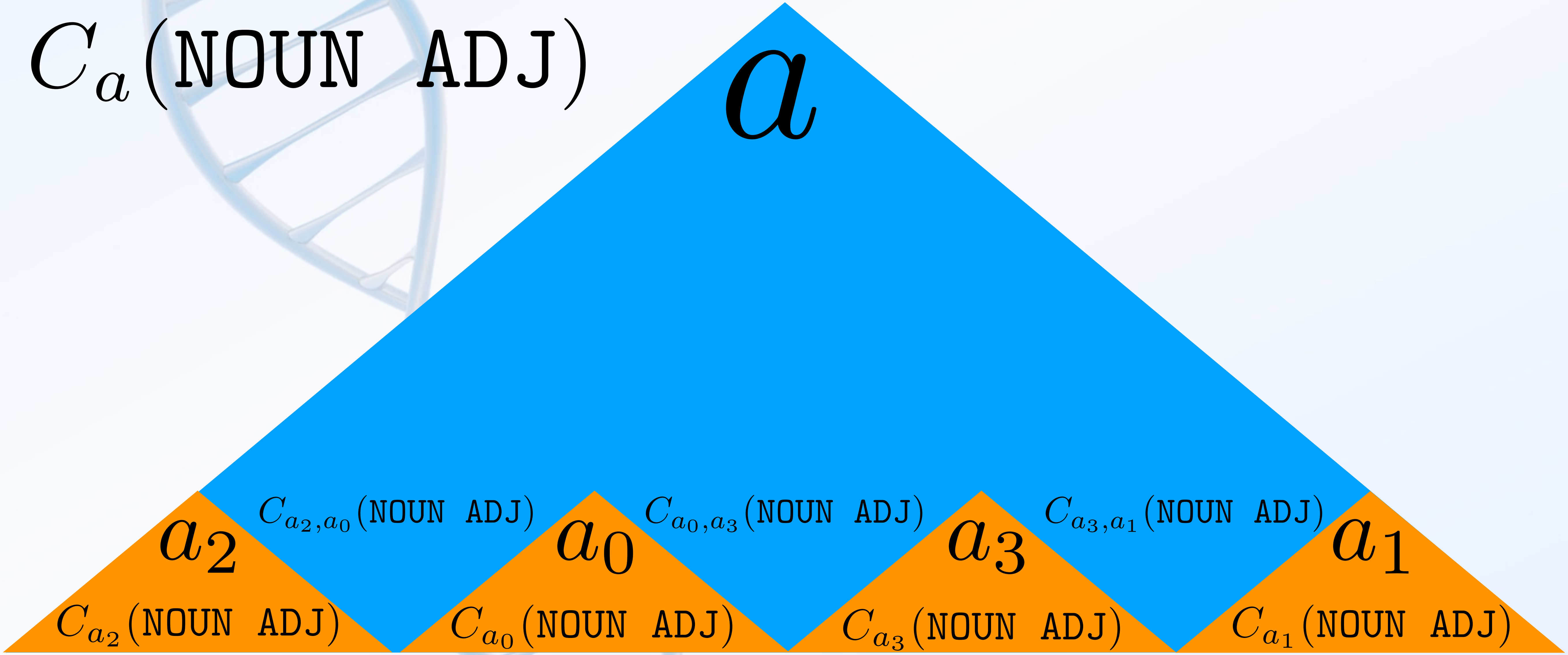
Computing the Expected Counts

by Dynamic Programming

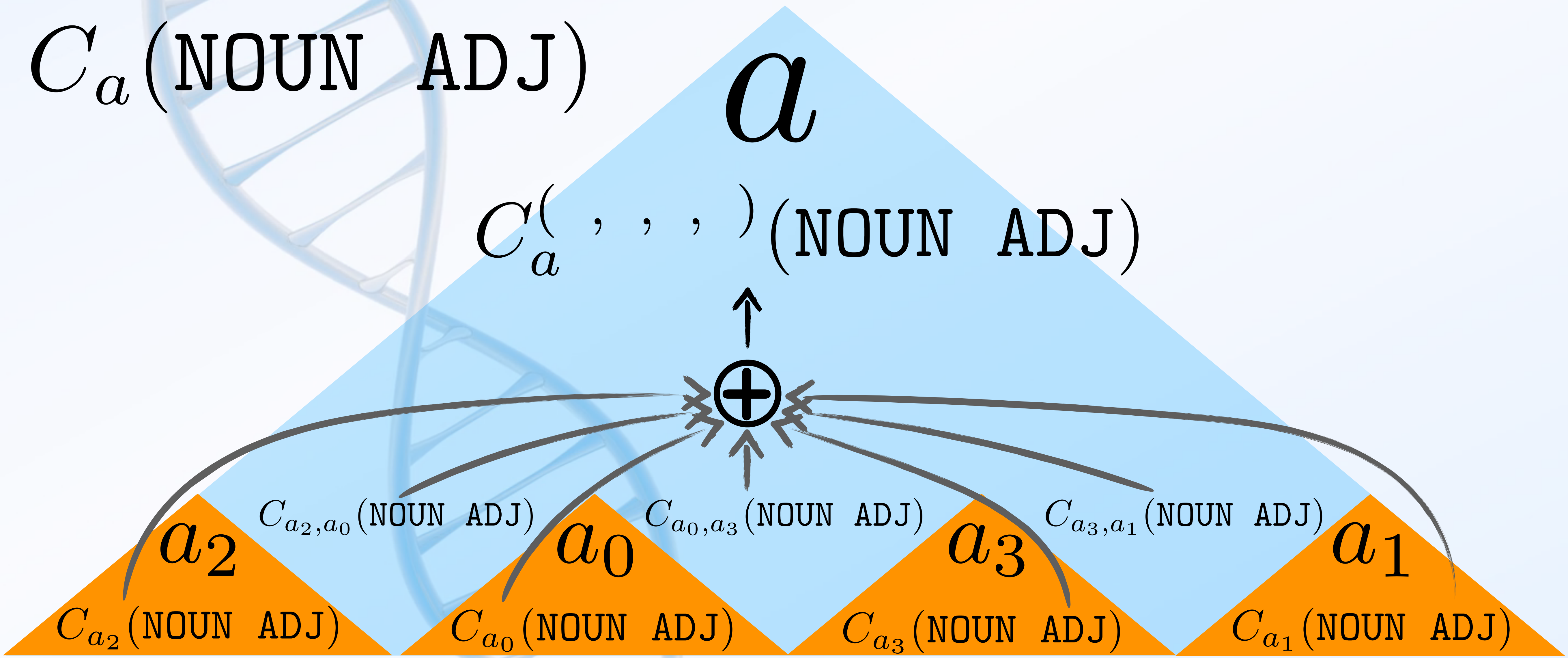
$C_a(\texttt{NOUN ADJ})$



Computing the Expected Counts

by Dynamic Programming

$C_a(\texttt{NOUN ADJ})$



Computing the Expected Counts

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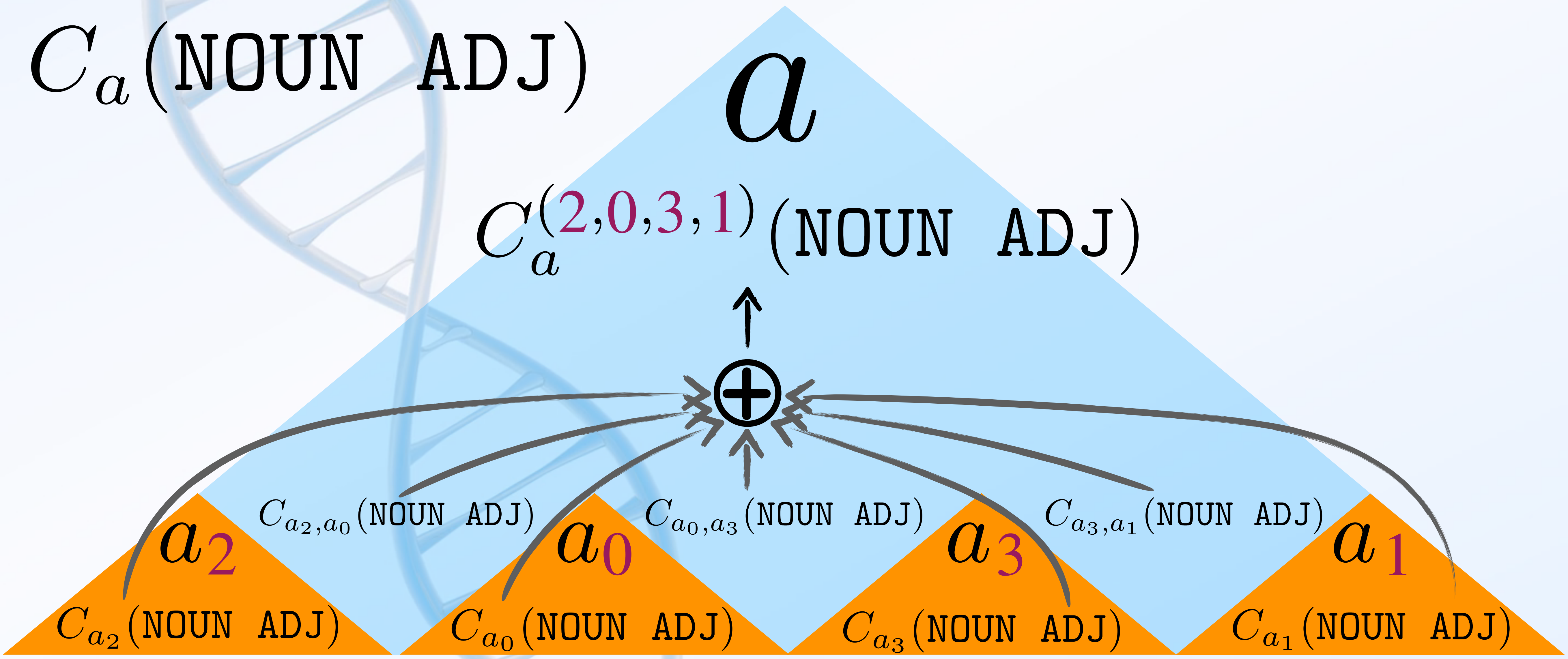
$C_a(\texttt{NOUN ADJ})$



Computing the Expected Counts

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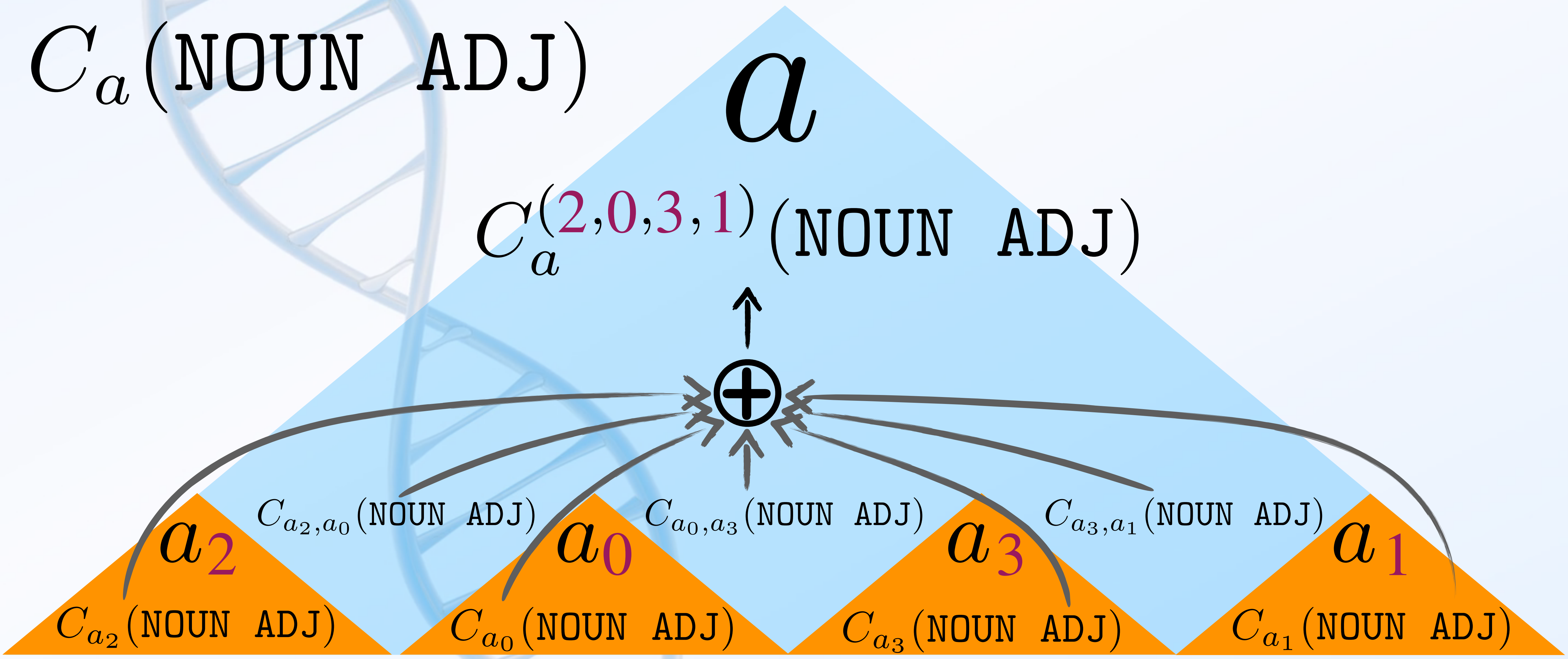
$C_a(\texttt{NOUN ADJ})$



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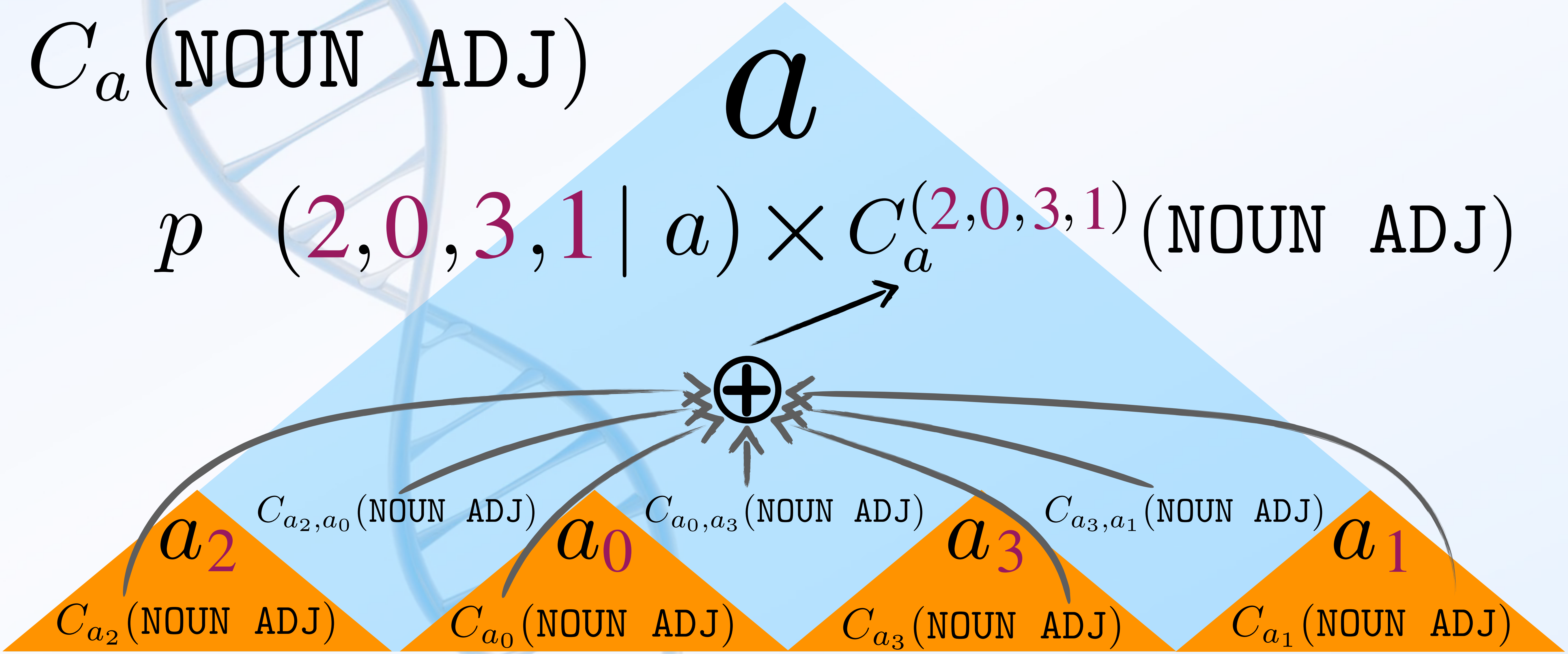
Computing the Expected Counts
by Dynamic Programming

$$C_a(\texttt{NOUN ADJ})$$

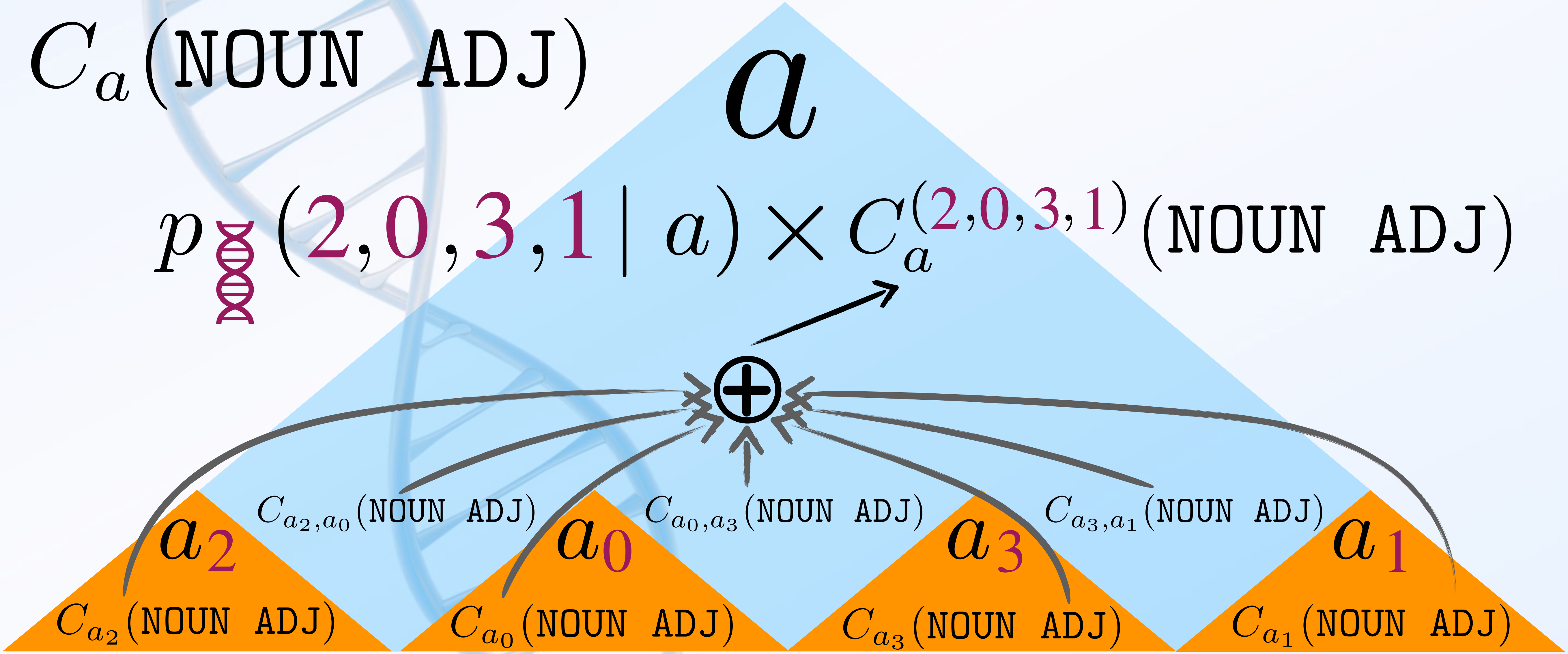
$$p\ (2,0,3,1 \mid a) \times C_a^{(2,0,3,1)}(\texttt{NOUN ADJ})$$



Computing the Expected Counts
by Dynamic Programming

$C_a(\texttt{NOUN ADJ})$

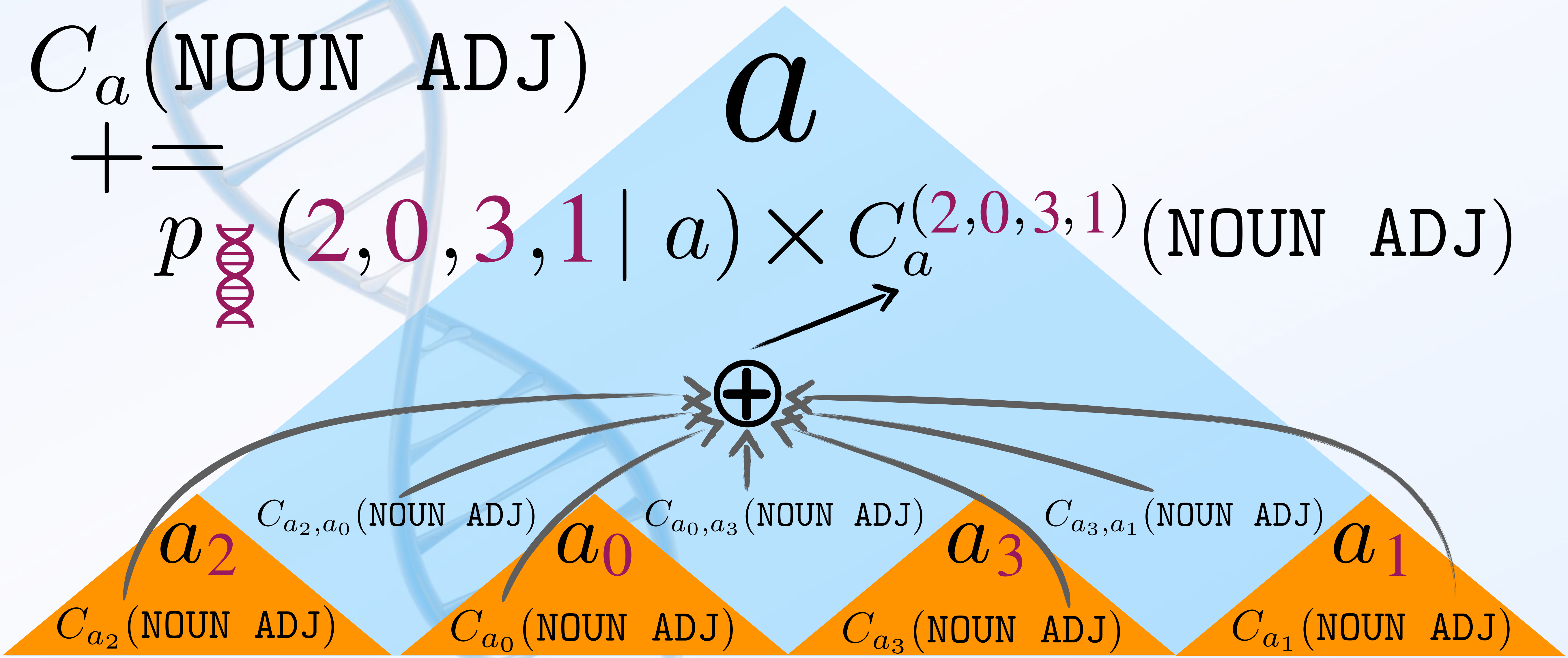
$p(2,0,3,1 \mid a) \times C_a^{(2,0,3,1)}(\texttt{NOUN ADJ})$



Computing the Expected Counts

by Dynamic Programming

$$C_a(\texttt{NOUN ADJ}) \mathrel{+}= p(2,0,3,1 \mid a) \times C_a^{(2,0,3,1)}(\texttt{NOUN ADJ})$$

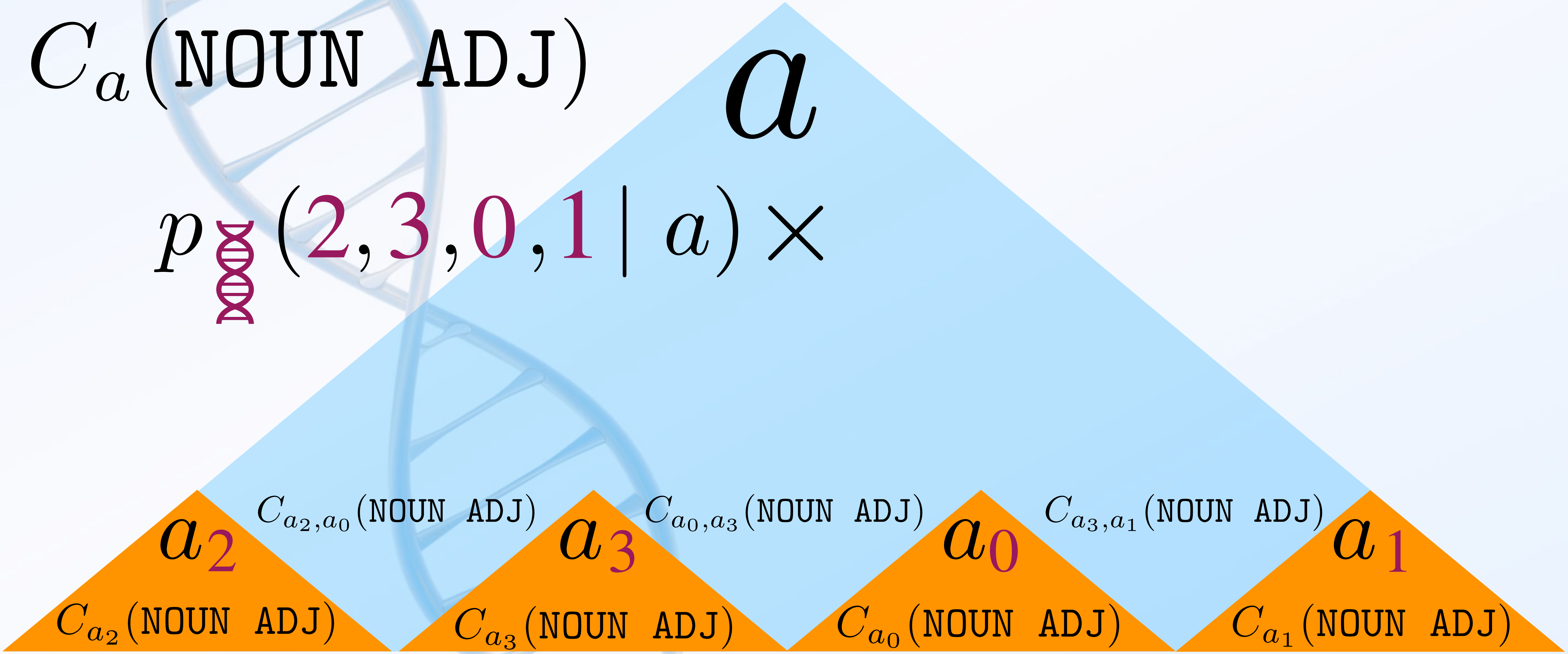


Computing the Expected Counts

by Dynamic Programming

$C_a(\texttt{NOUN ADJ})$

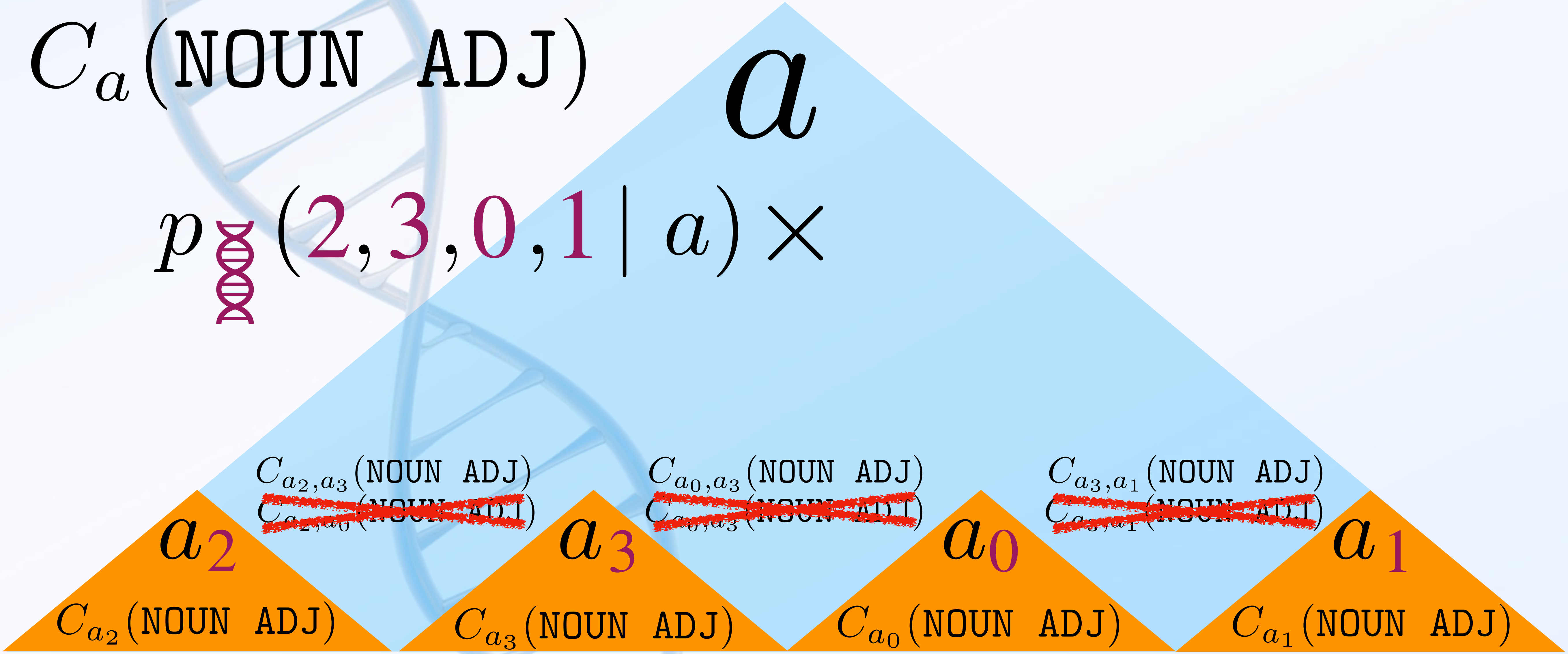
$p_{🧬}(2,3,0,1 \mid a) \times$



Computing the Expected Counts

by Dynamic Programming

$C_a(\texttt{NOUN ADJ})$



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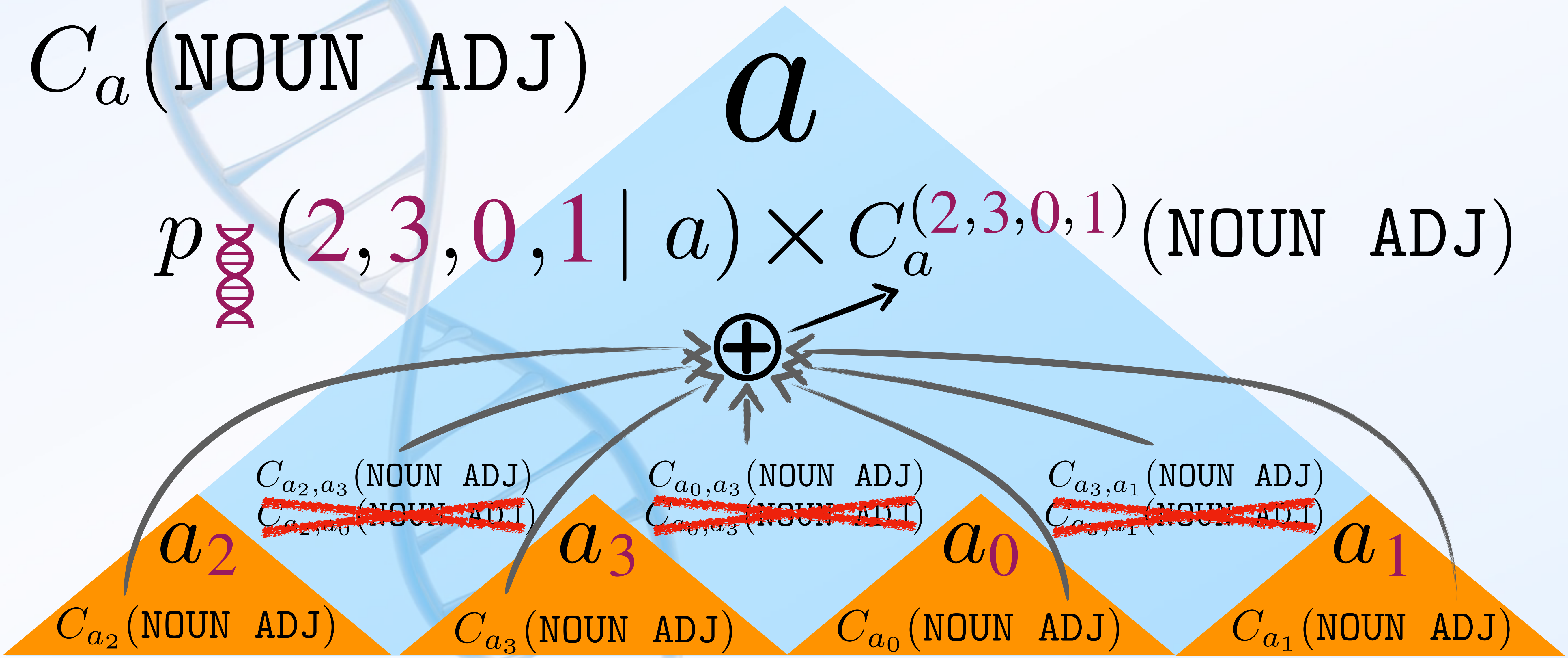
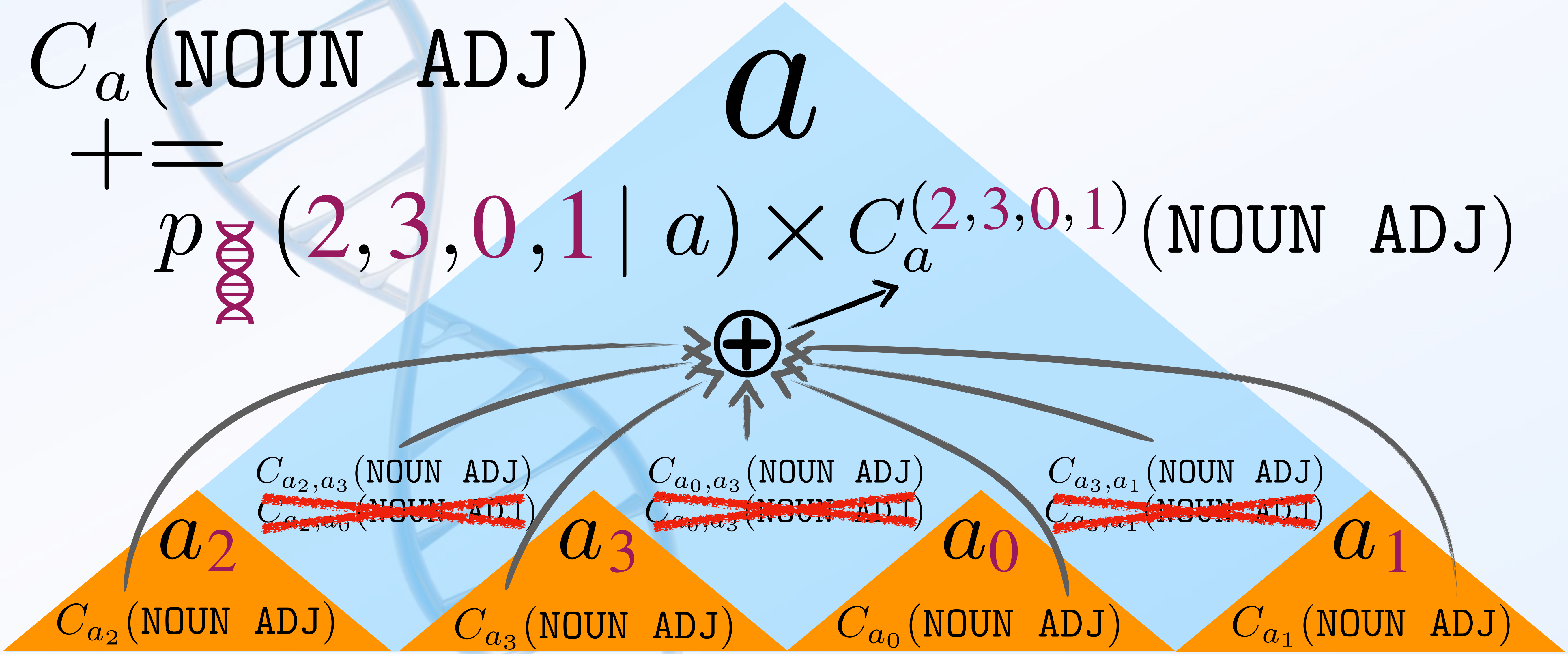
Computing the Expected Counts
by Dynamic Programming



Computing the Expected Counts

by Dynamic Programming

$$C_a(\texttt{NOUN ADJ}) \mathrel{+}= p(2,3,0,1 \mid a) \times C_a^{(2,3,0,1)}(\texttt{NOUN ADJ})$$



Computing the Expected Counts
by Dynamic Programming

$C_a(\texttt{NOUN ADJ})$

a

$p(3, 2, 0, 1 \mid a) \times$

$C_{a_2,a_3}(\texttt{NOUN ADJ})$ $\cancel{C_{a_2,a_0}(\texttt{NOUN ADJ})}$

$C_{a_0,a_3}(\texttt{NOUN ADJ})$ $\cancel{C_{a_0,a_3}(\texttt{NOUN ADJ})}$

$C_{a_3,a_1}(\texttt{NOUN ADJ})$ $\cancel{C_{a_3,a_1}(\texttt{NOUN ADJ})}$

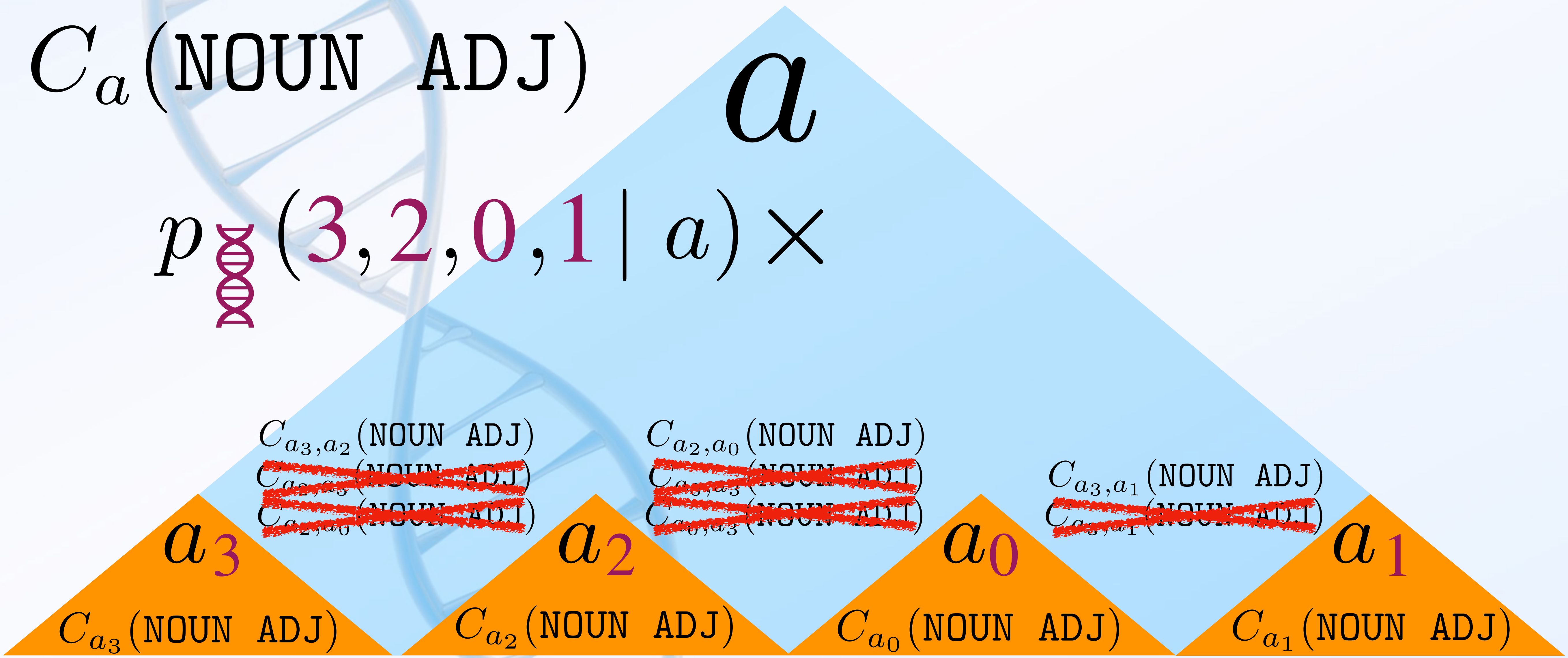
a_3 a_2 a_0 a_1

$C_{a_3}(\texttt{NOUN ADJ})$ $C_{a_2}(\texttt{NOUN ADJ})$ $C_{a_0}(\texttt{NOUN ADJ})$ $C_{a_1}(\texttt{NOUN ADJ})$

Computing the Expected Counts

by Dynamic Programming

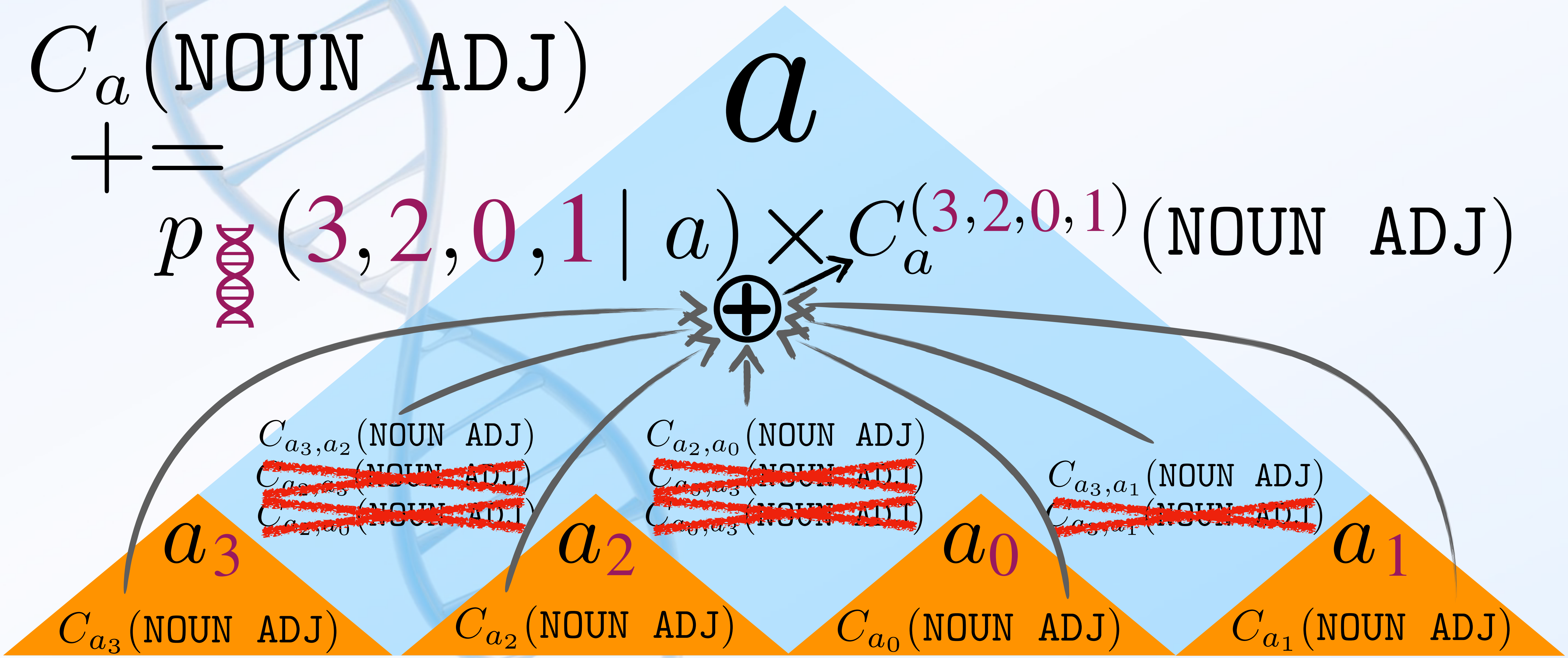
$C_a(\texttt{NOUN ADJ})$



Computing the Expected Counts

by Dynamic Programming

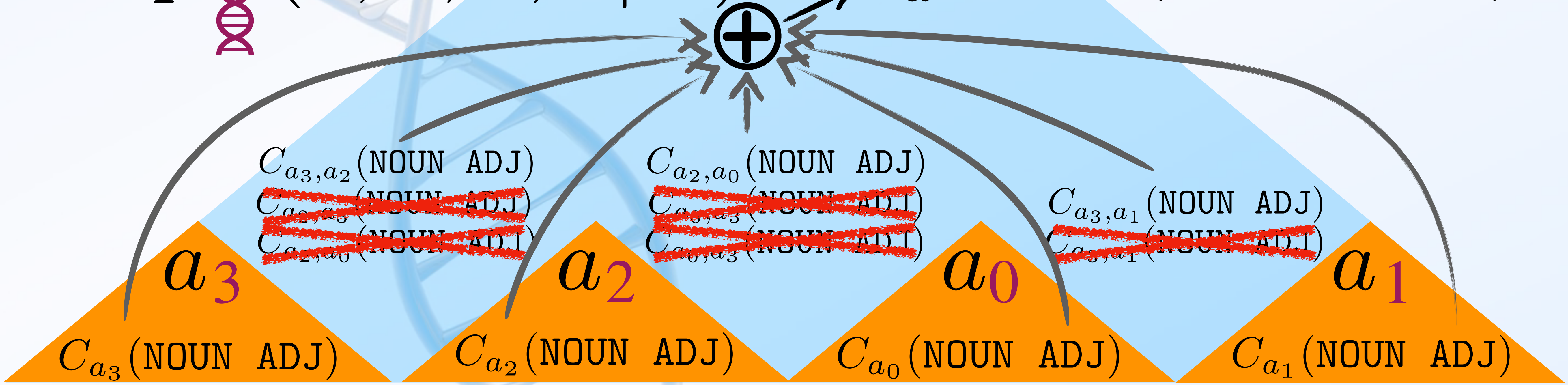
$$C_a(\texttt{NOUN ADJ}) \mathrel{+}= p_{\text{🧬}}(3,2,0,1 \mid a) \times C_a^{(3,2,0,1)}(\texttt{NOUN ADJ})$$



Computing the Expected Counts

by Dynamic Programming

$$C_a(\texttt{NOUN ADJ}) \mathrel{+}= p(3,2,0,1 \mid a) \times C_a^{(3,2,0,1)}(\texttt{NOUN ADJ})$$



4! Permutations

Data

- Universal Dependencies version 1.2
  - A collection of 37 dependency treebanks for 33 languages.

Train	Test
cs, es, fr, hi, de, it, la_itt, no, ar, pt, en, nl, da, fi, got, grc, et, la_proiel, grc_proiel, bg	la, hr, ga, he, hu, fa, ta, cu, el, ro, sl, ja_ktc, sv, fi_ftb, id, eu, pl

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Is your method work?

Is your method work?

Overall YES!

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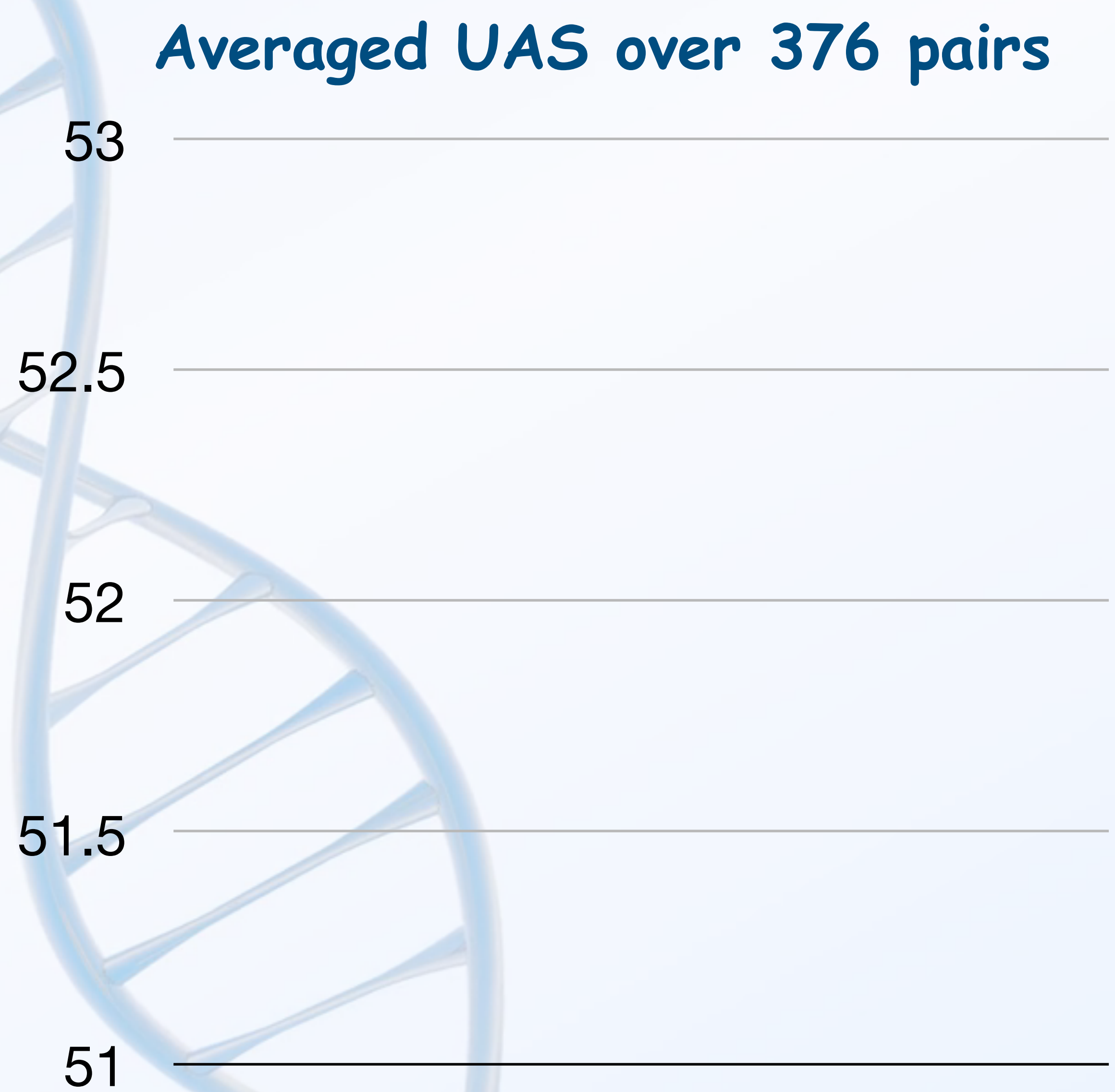
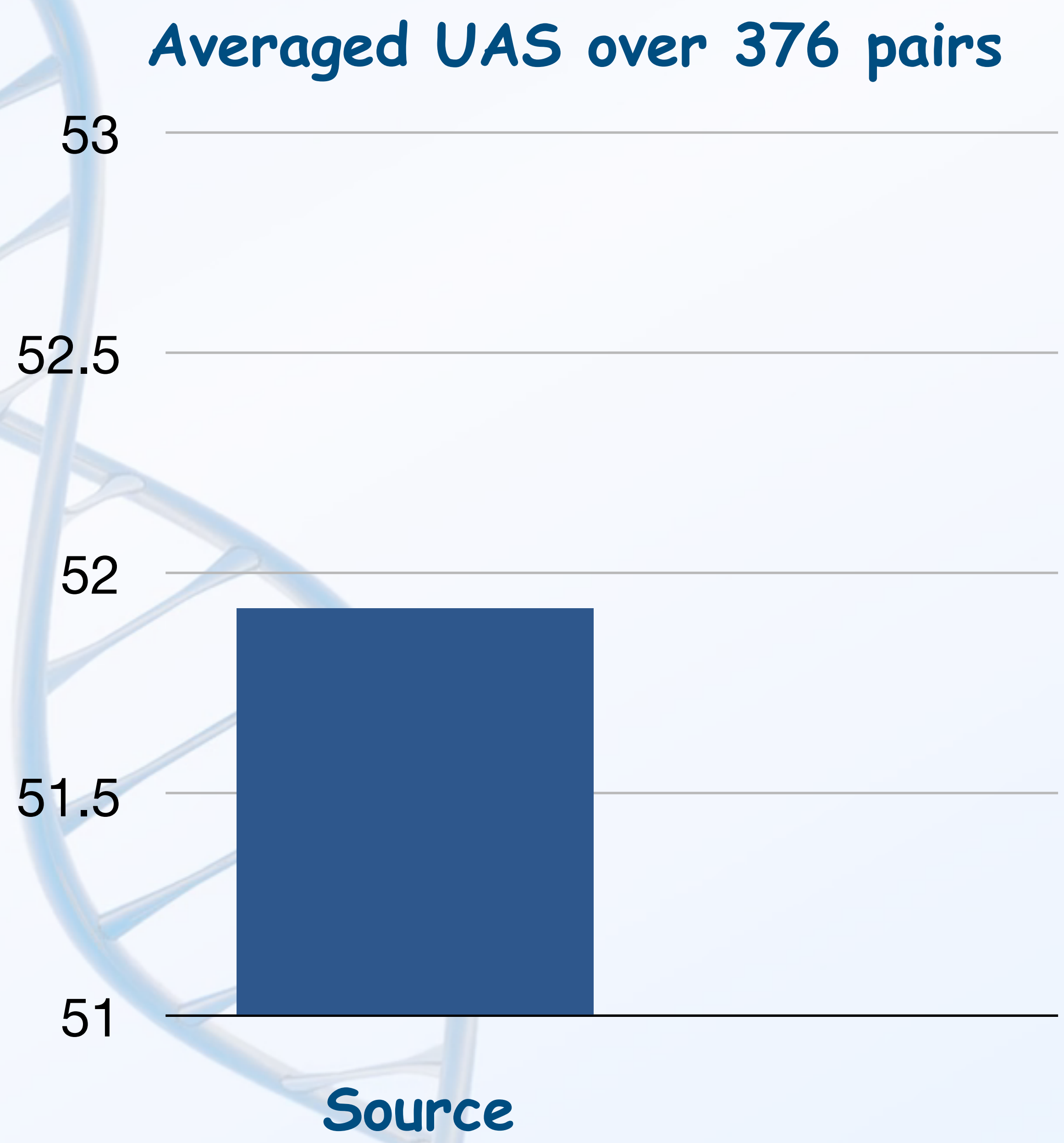
Is your method work?



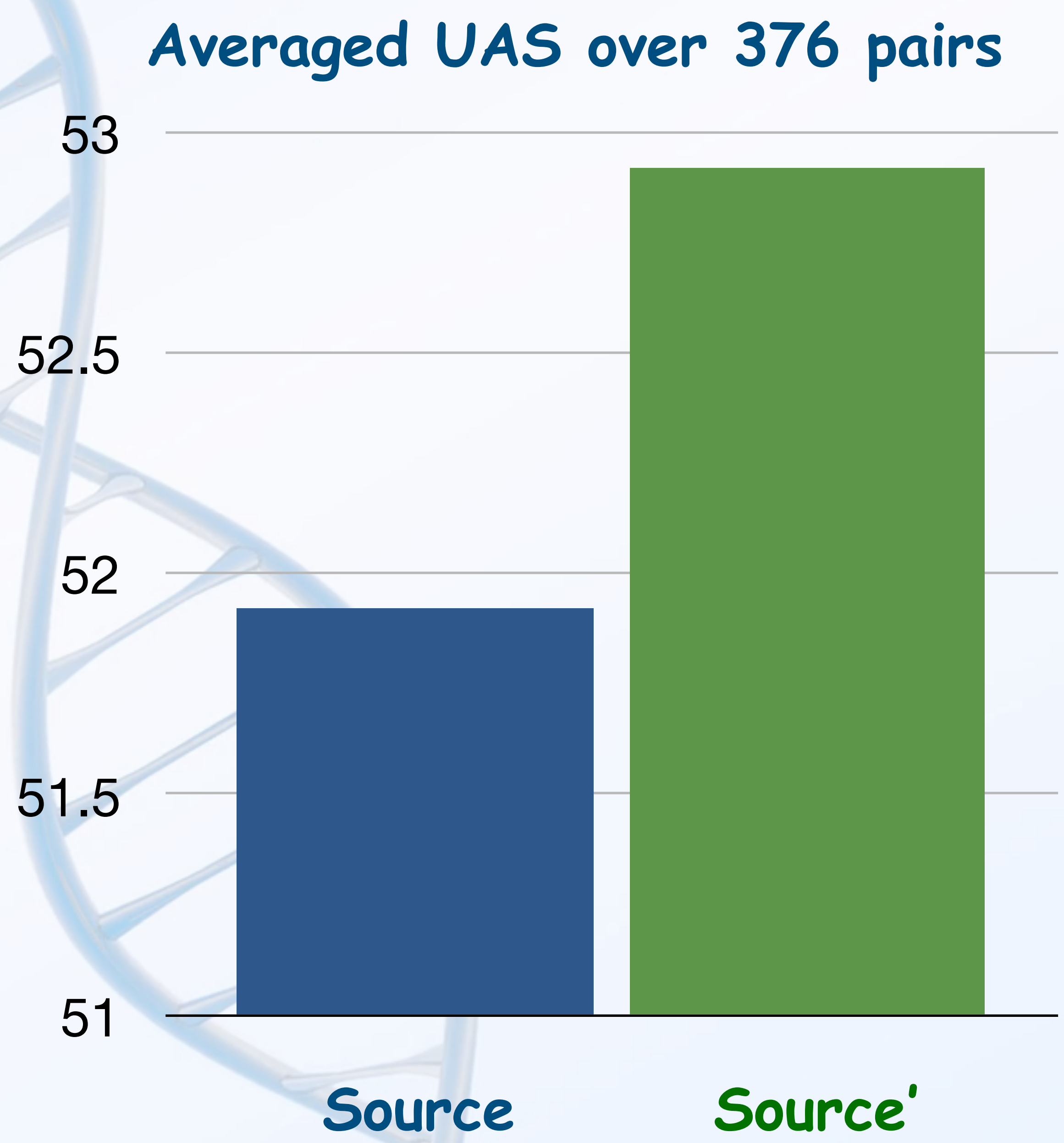
Overall YES!

Is your method work?

Overall YES!



Is your method work?



Overall YES!

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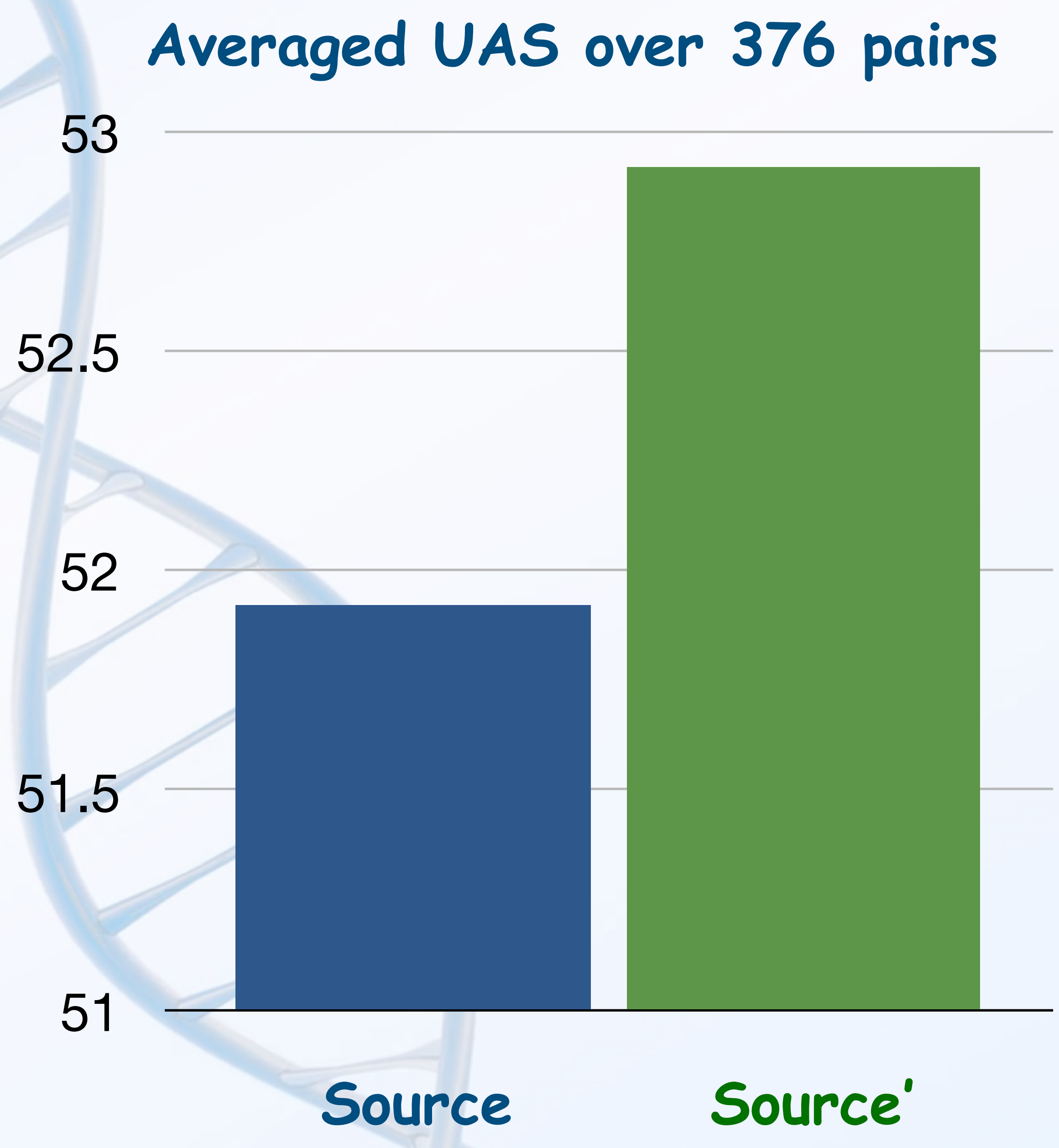
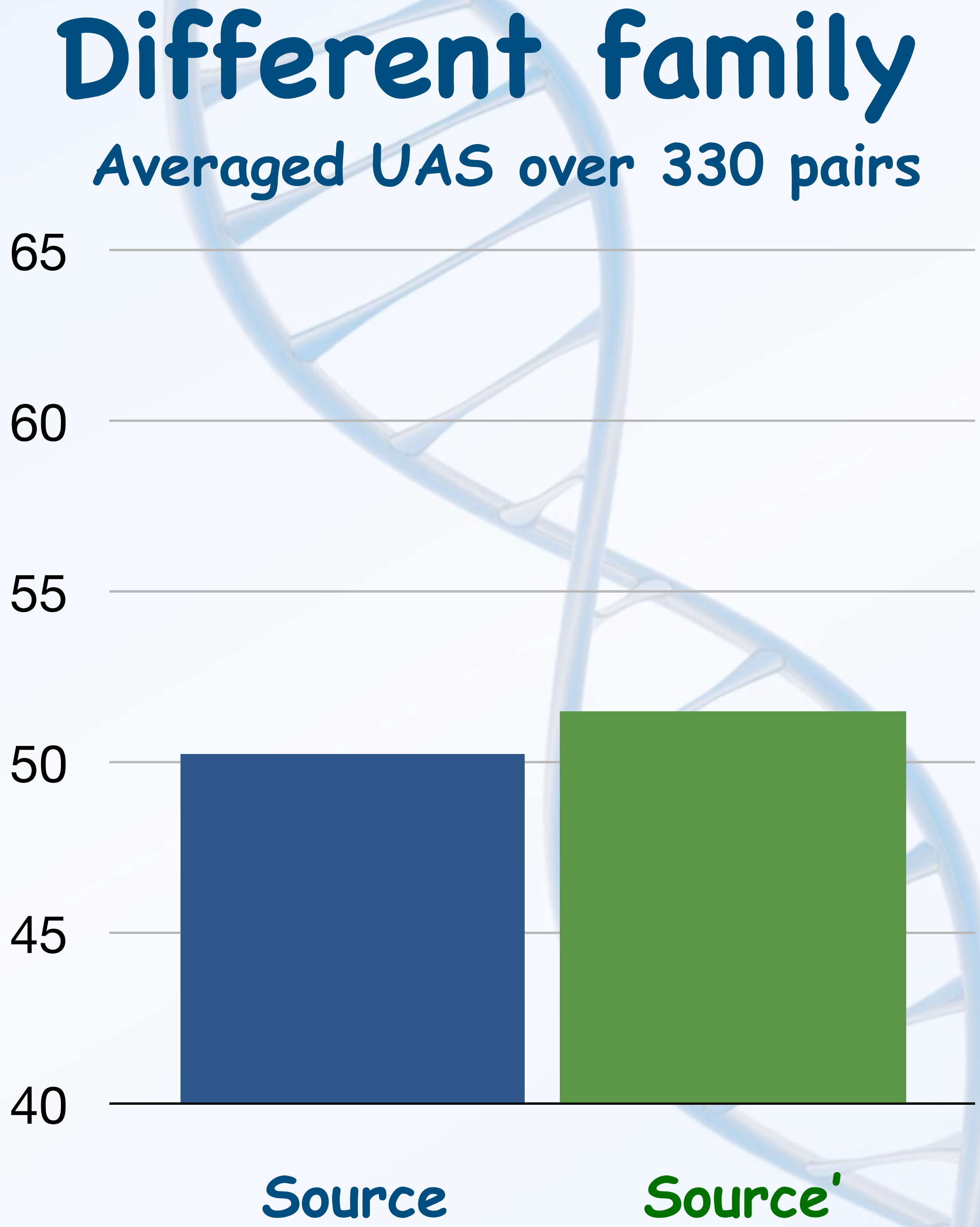
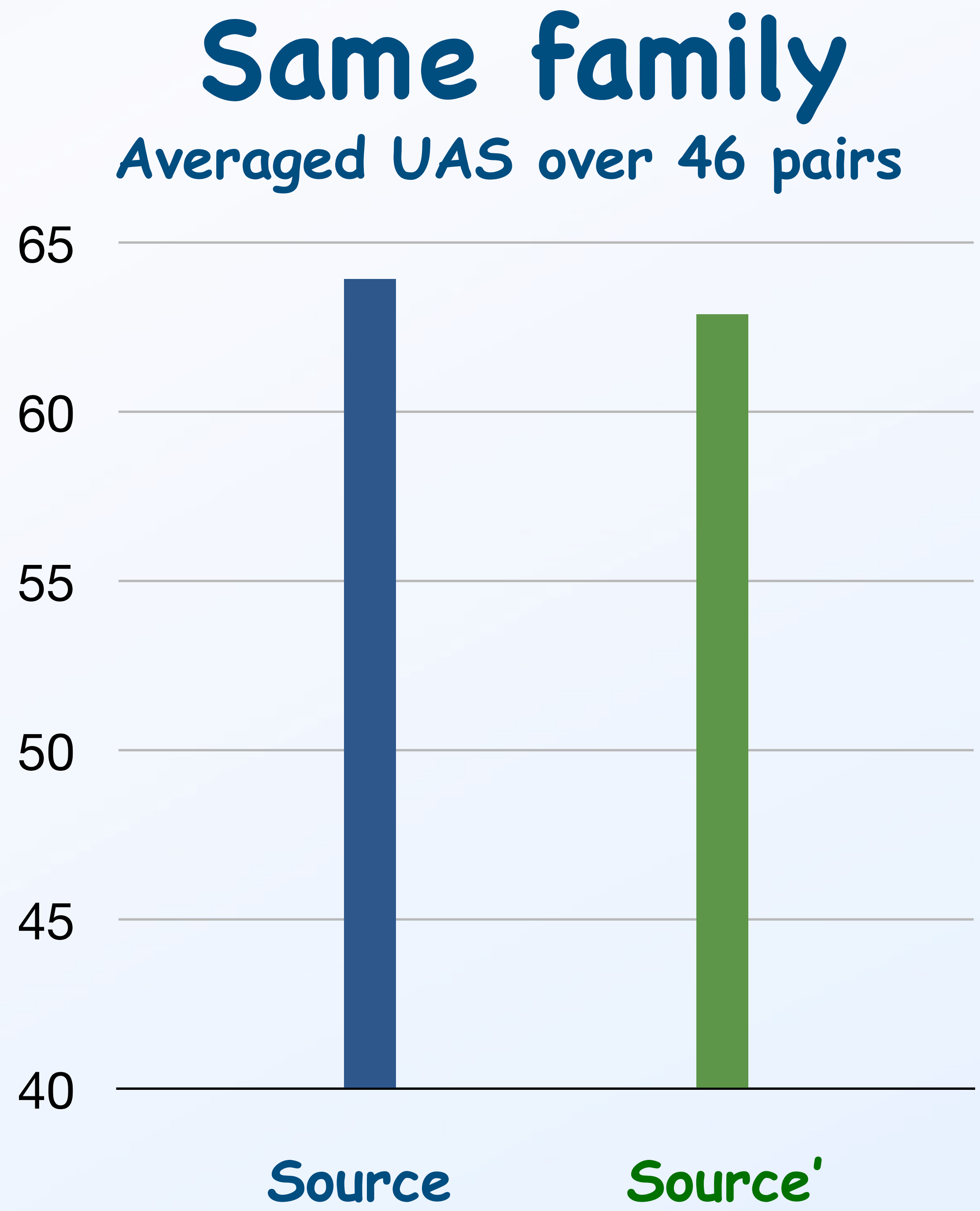
Depends on the language family

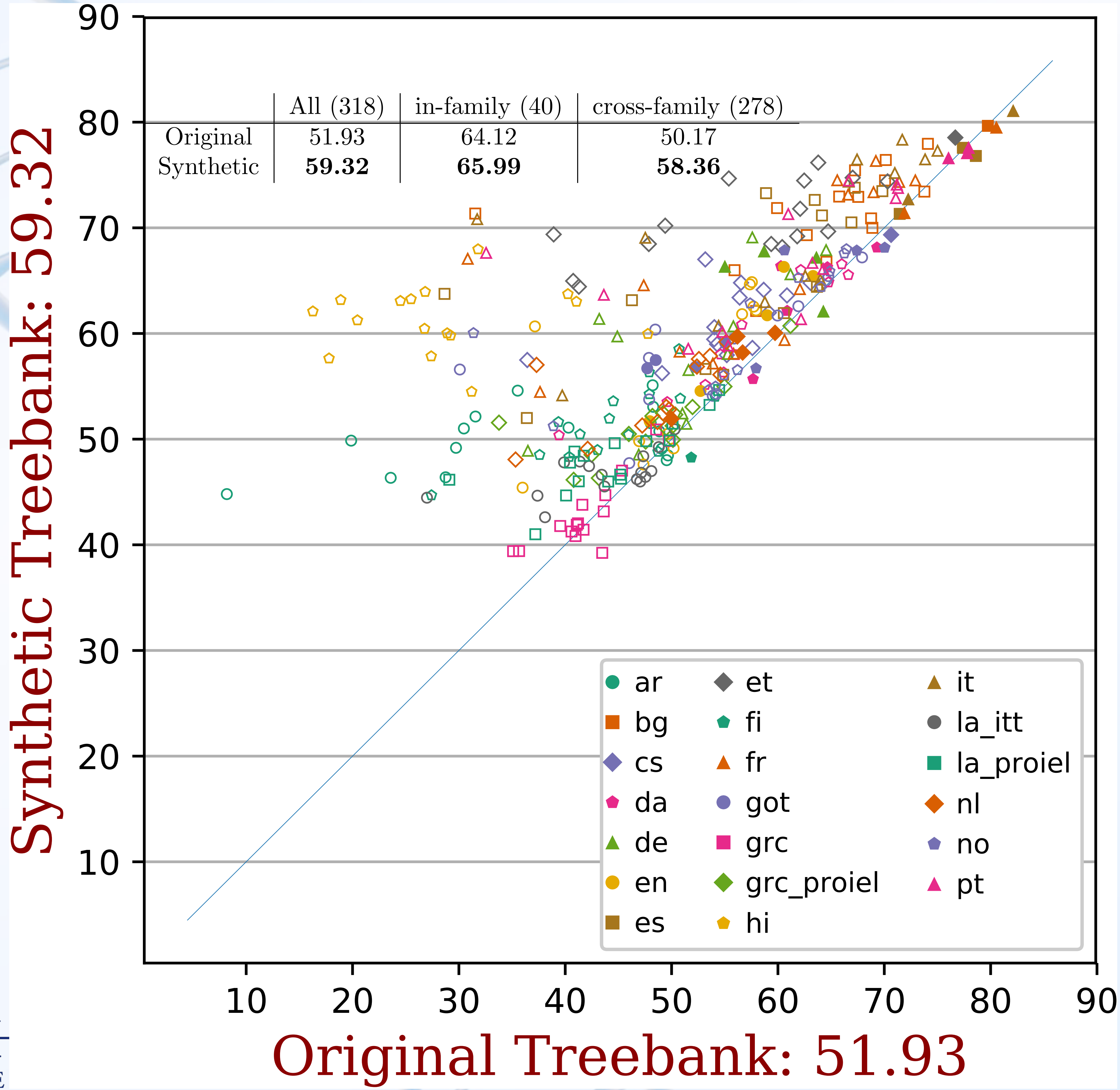


Depends on the language family





Oracle Realization



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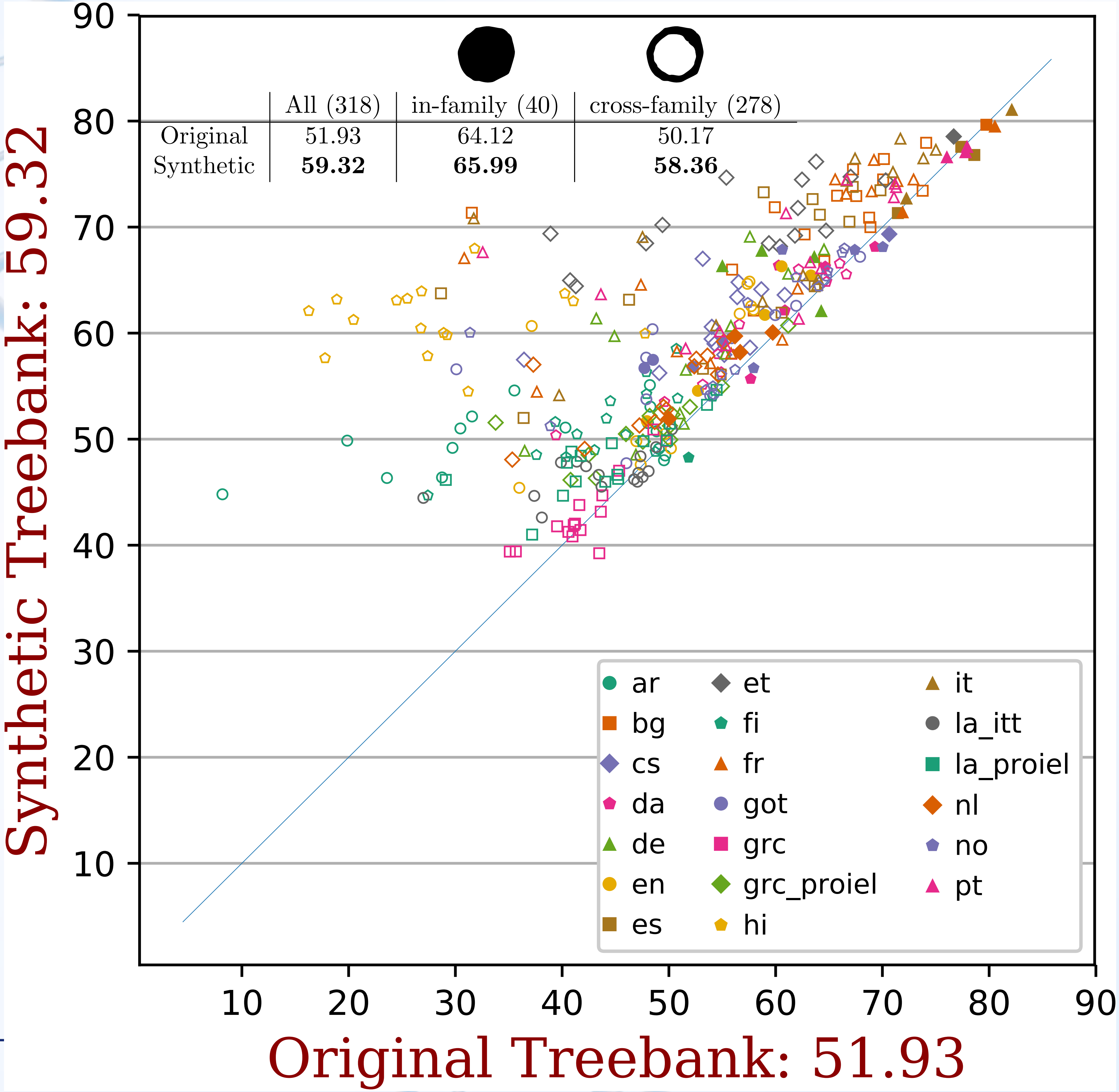

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SVO or OVS ?

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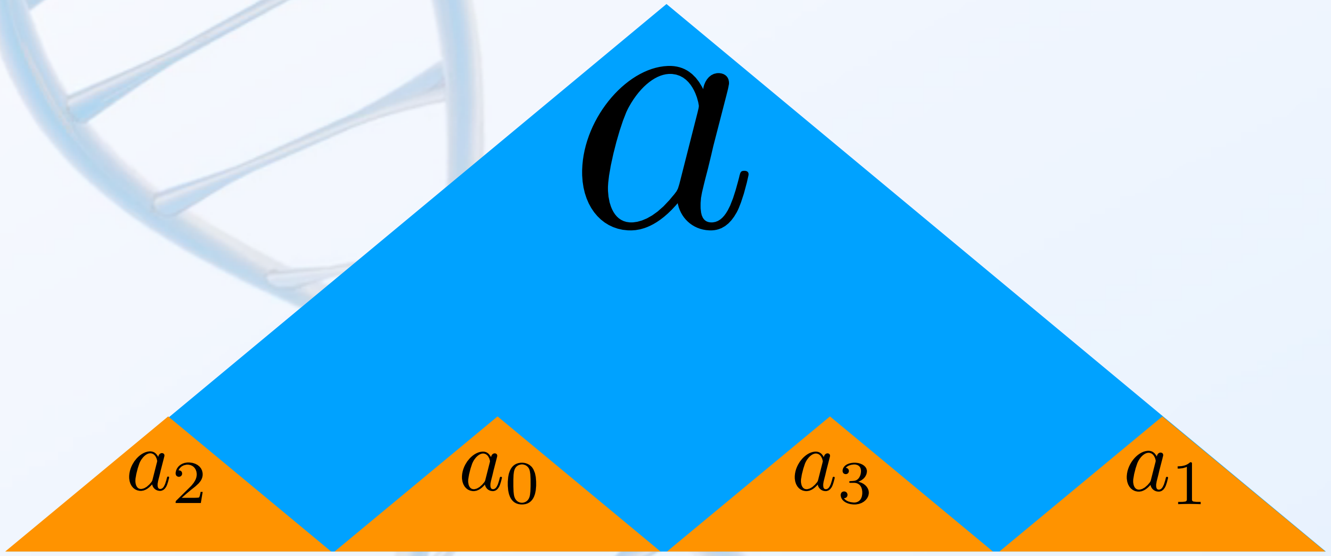

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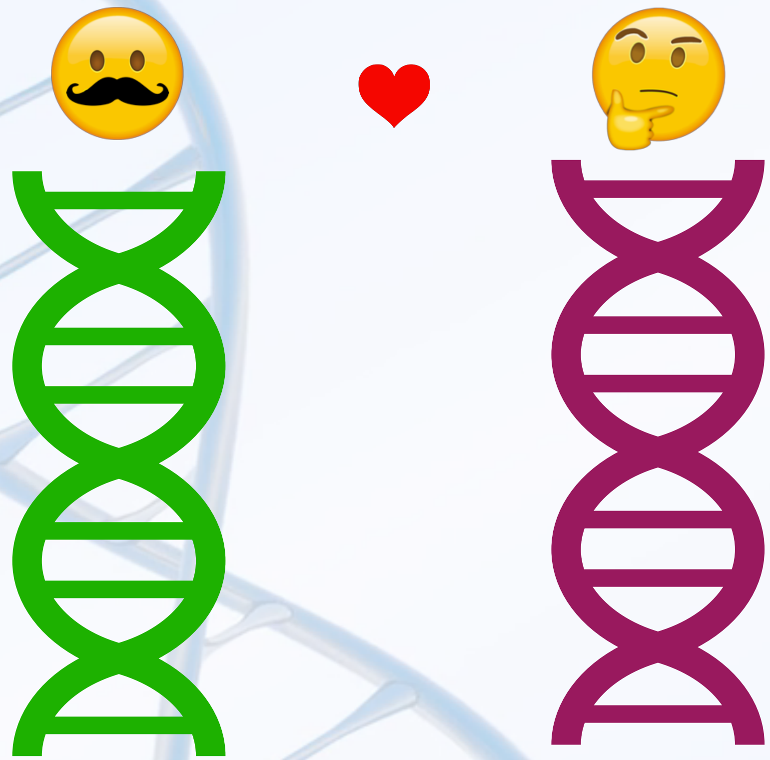
- Multi-sources!
  - One parser on many languages (Ammar et al. 2016, **our poster tomorrow**)

Wang and Eisner (2016)

Source1 Source2



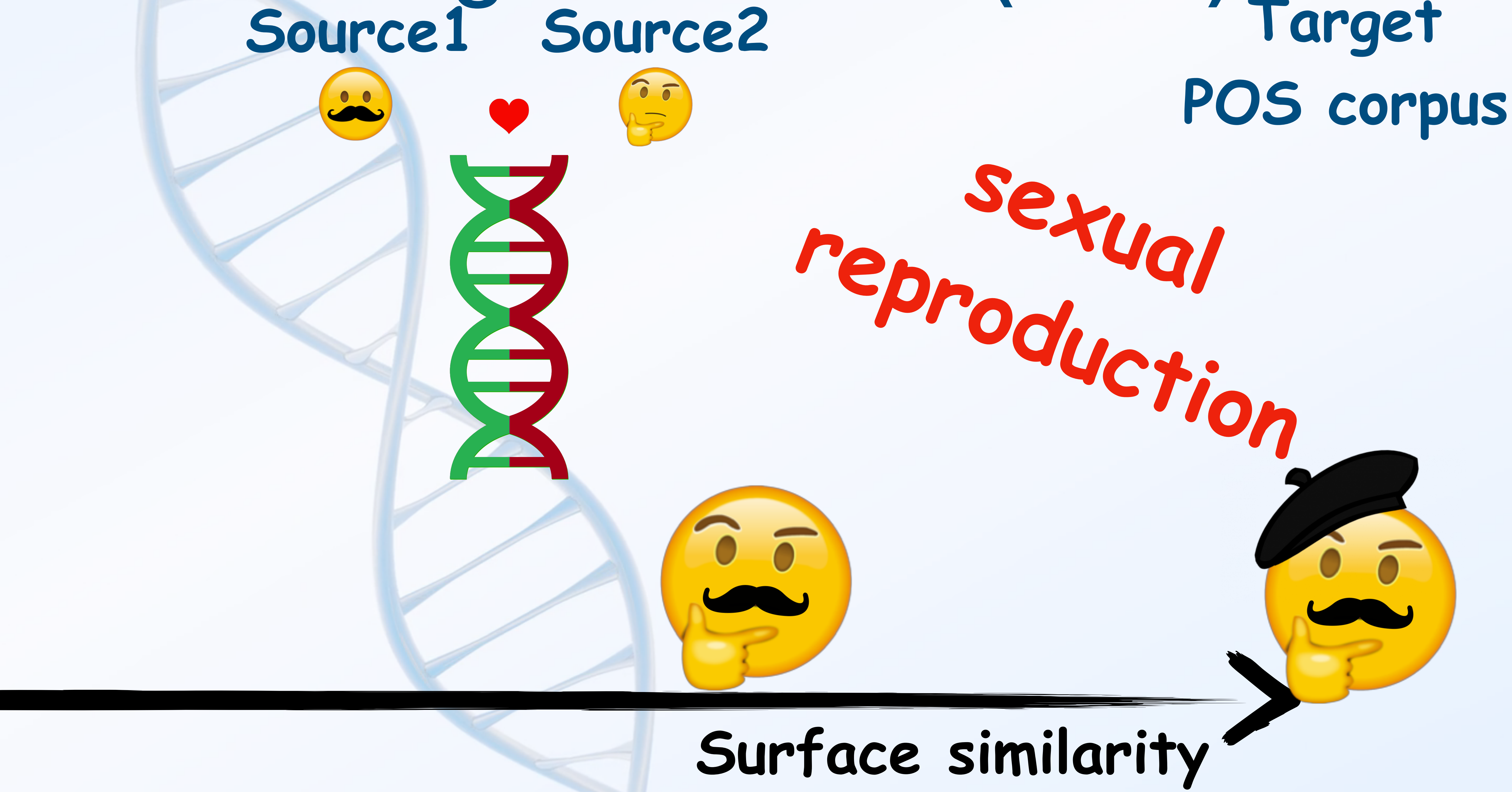
Target

POS corpus

sexual reproduction

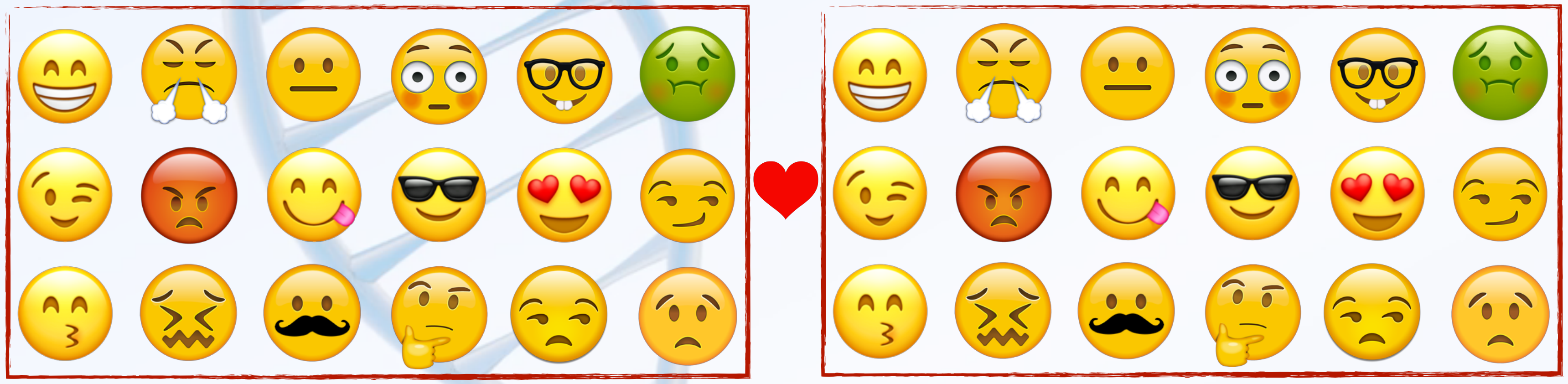
Surface similarity

Wang and Eisner (2016)



Wang and Eisner (2016)

Source languages



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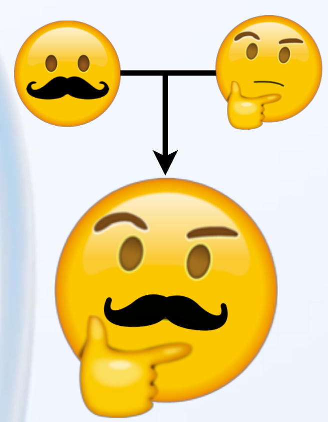

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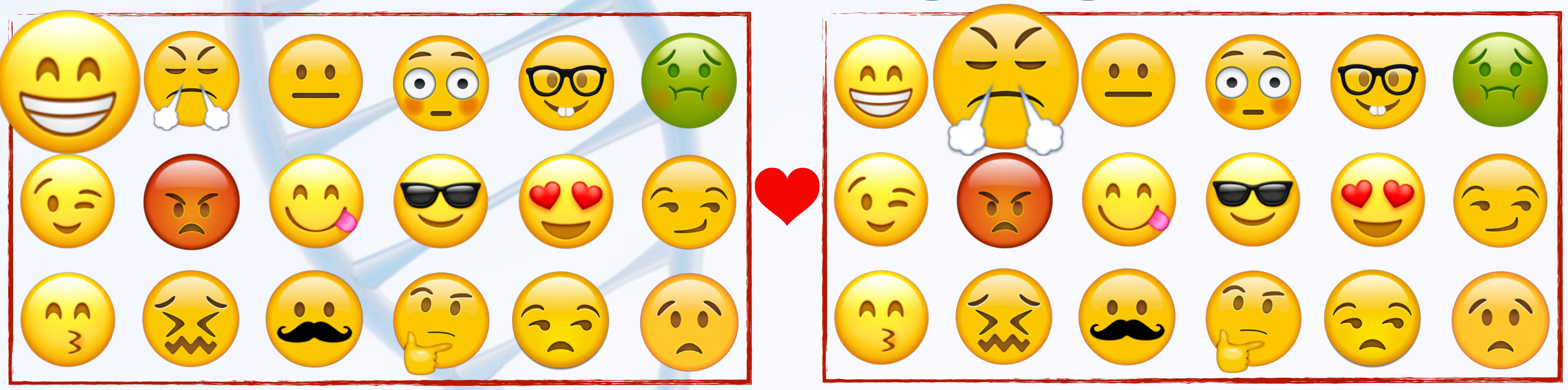

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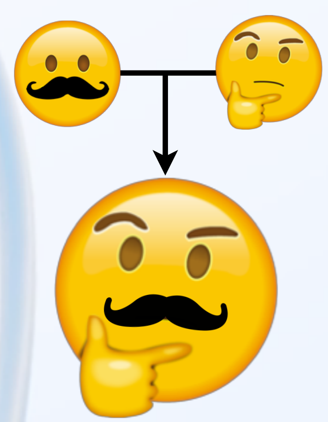

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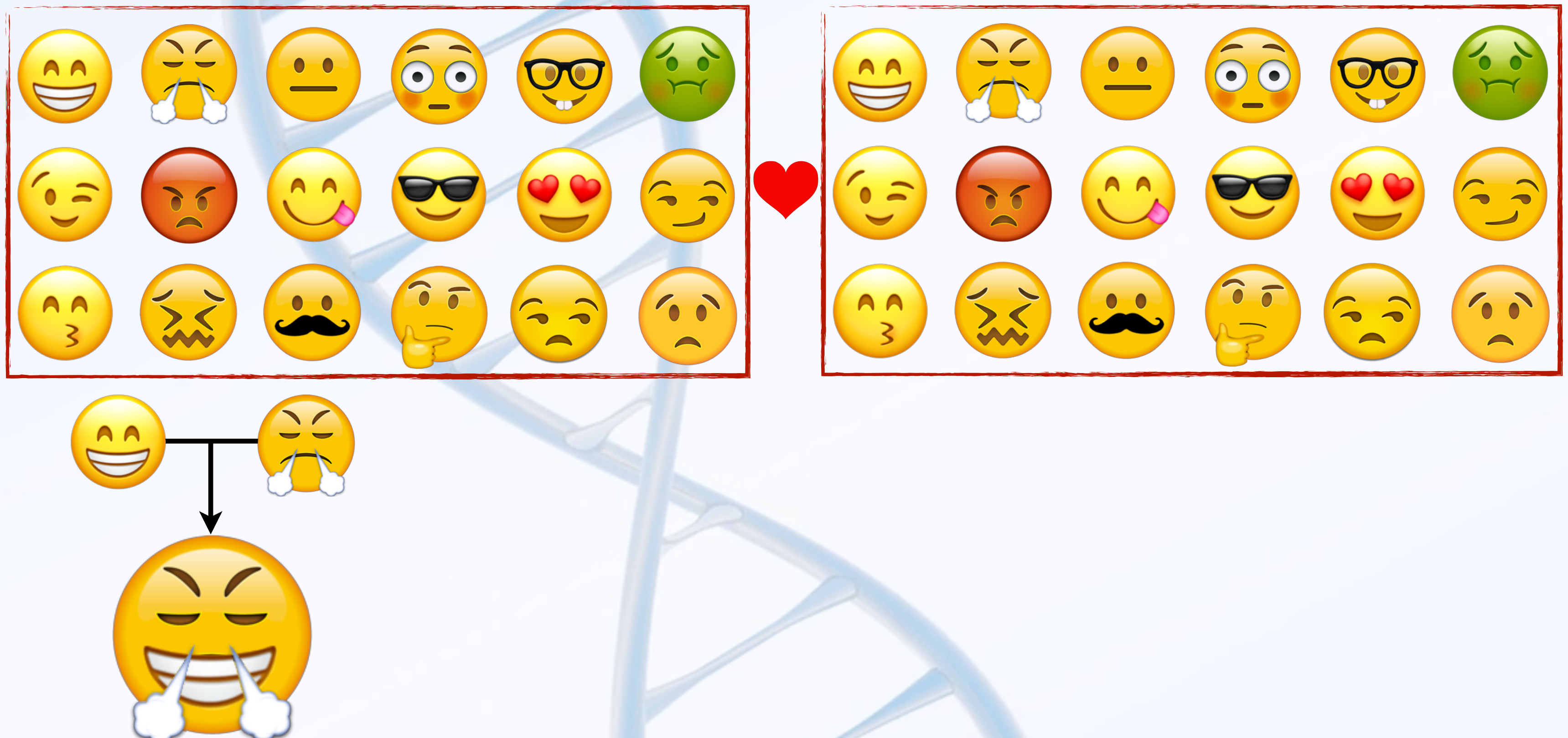

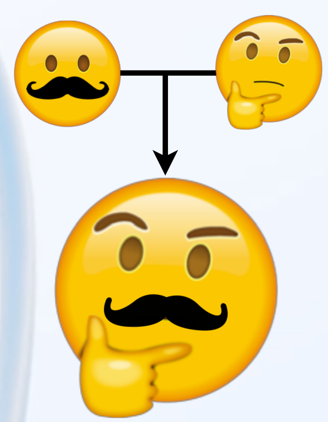

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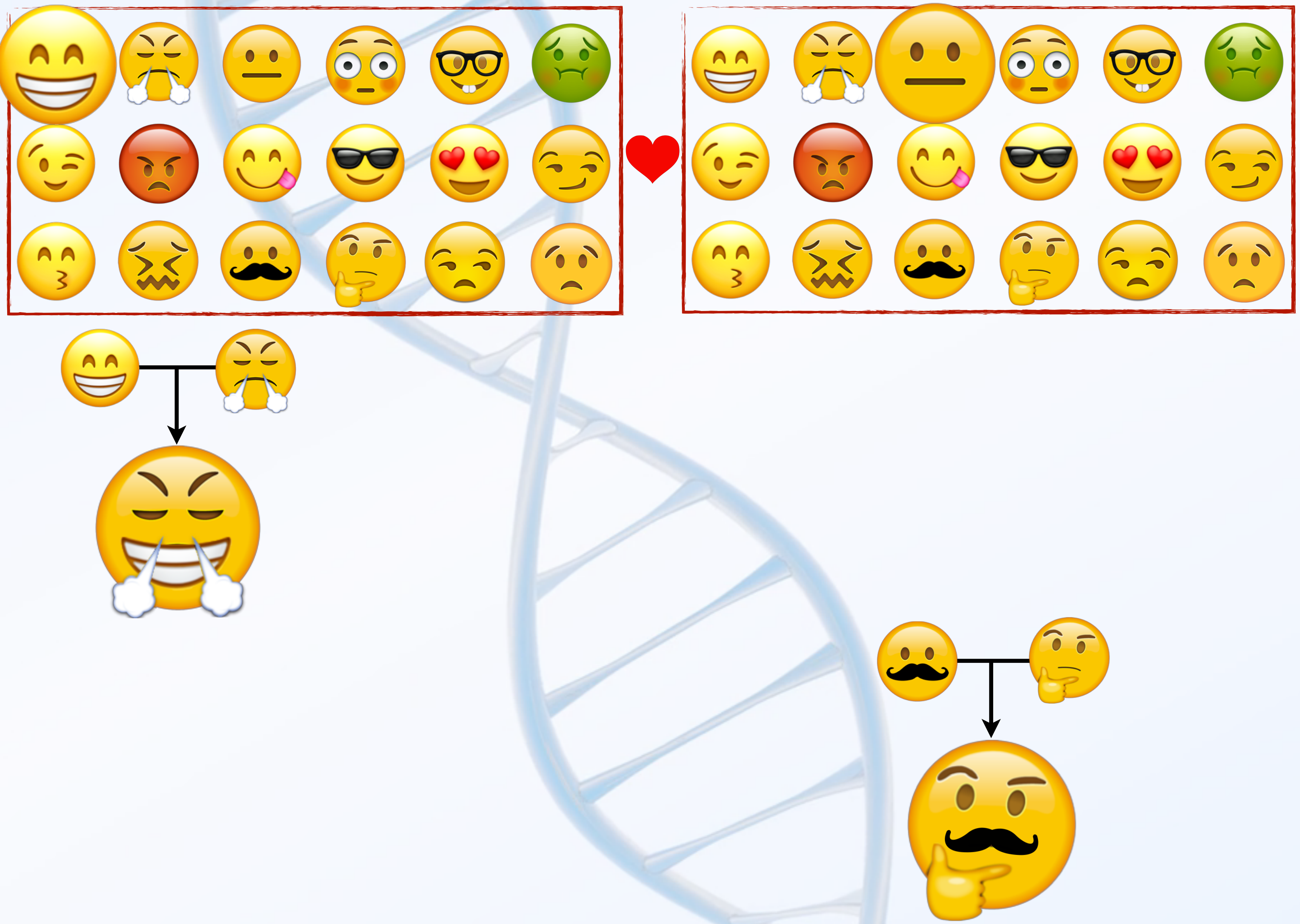

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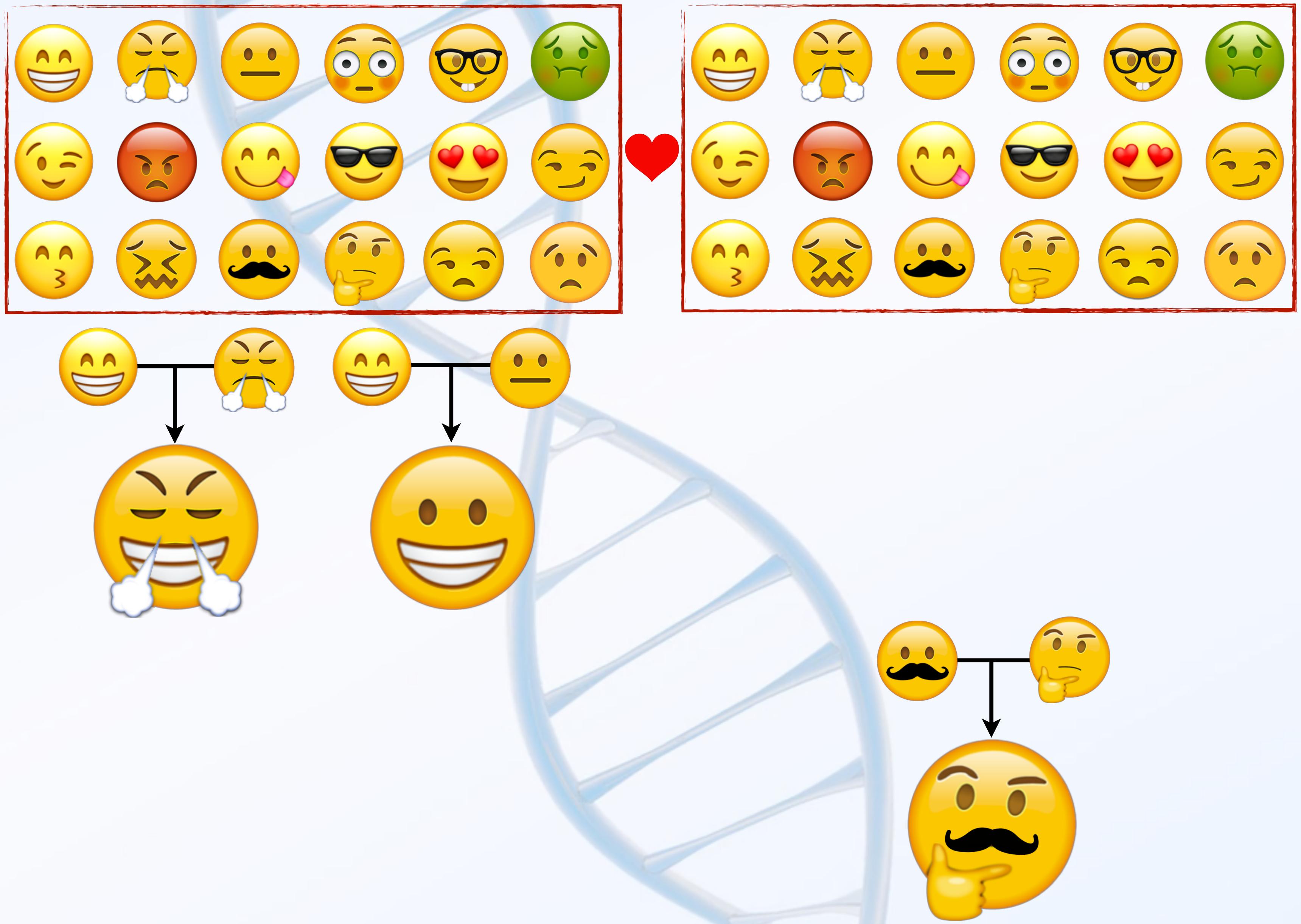

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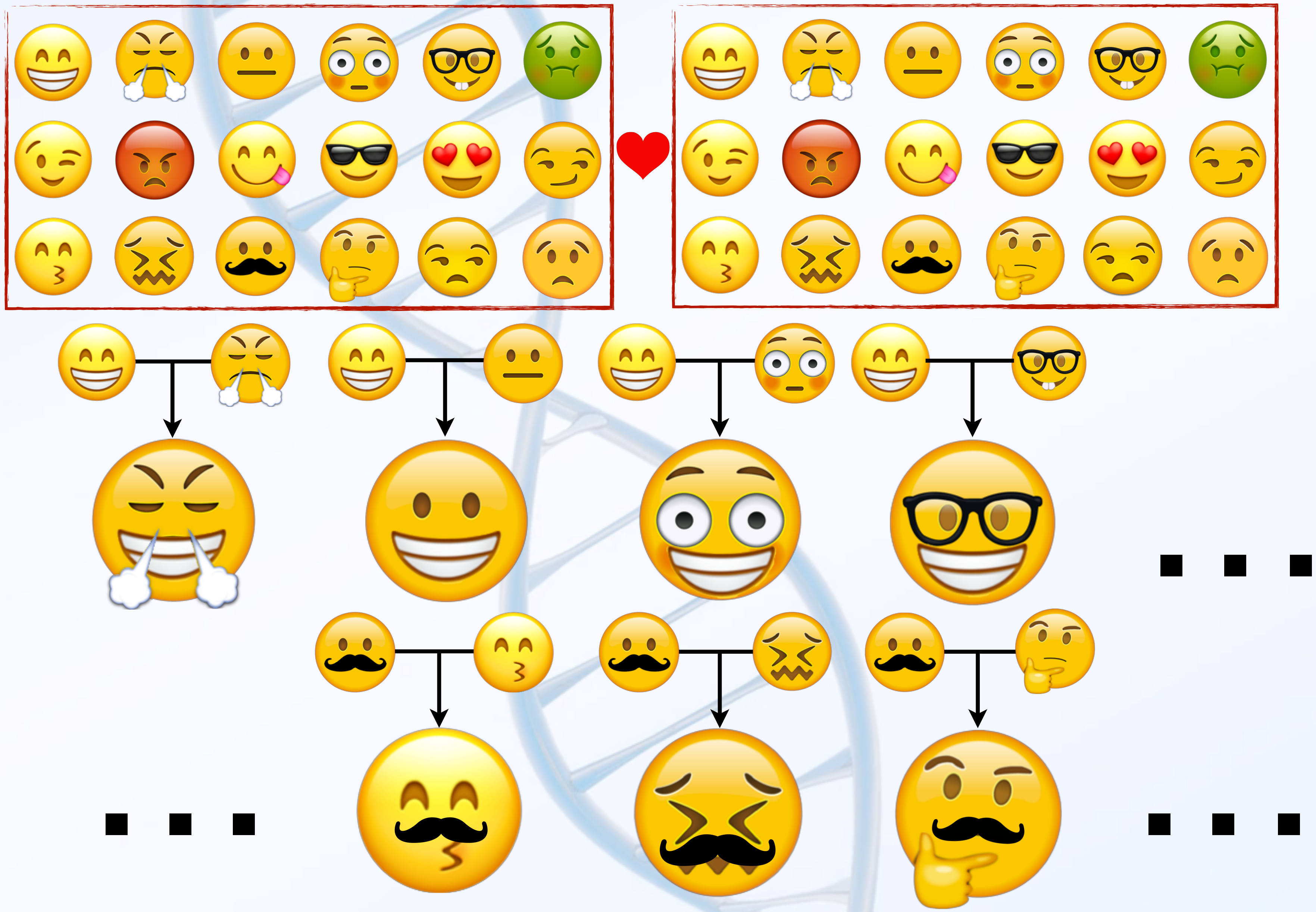

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Wang and Eisner, **Surface statistics of an unknown language indicate how to parse it.** TACL 2018

11:00-12:30, Saturday, Grand Hall 2

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THANKS!