# Do deep neural networks improve functional annotation of alpha-cyanobacteria?

#### Juliana SILVA BERNARDES

https://scholar.google.com/citations?user=a-ZYwhEAAAAJ&hl=en

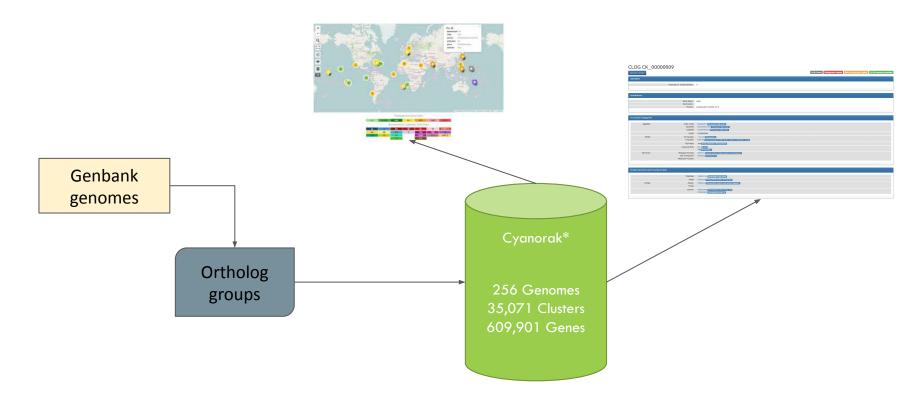
https://www.lcqb.upmc.fr/julianab/



### Why α-Cyanobacteria?

- Phototrophic microorganisms, appeared 3.5 billion years ago
- Responsible for the apparition of Oxygen on Earth
- One of the most diverse/widely distributed prokaryotic phyla
- Colonize both terrestrial and aquatic environments
- Origin of land plants /marine algae over the next millions of years
- They are most abundant photosynthetic organisms in the ocean and large lakes.

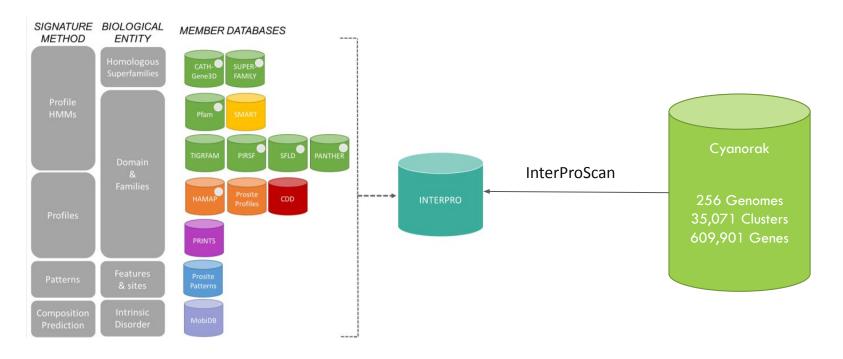
# Cyanorak



<sup>\*</sup>https://academic.oup.com/nar/article/49/D1/D667/5943826

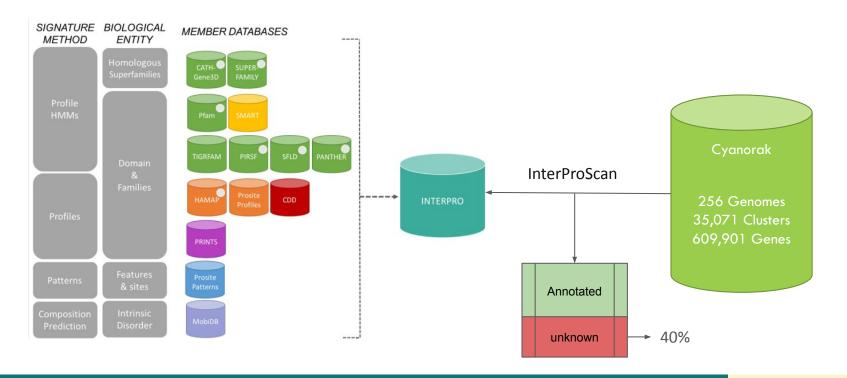
#### **Functional Annotation**

• Functional annotation of  $\alpha$ -Cyanobacteria is based on Interpro database



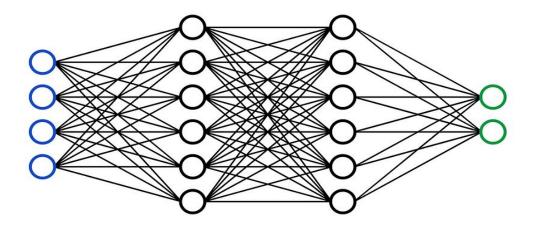
#### **Functional Annotation**

• Functional annotation of α-Cyanobacteria is based on Interpro database

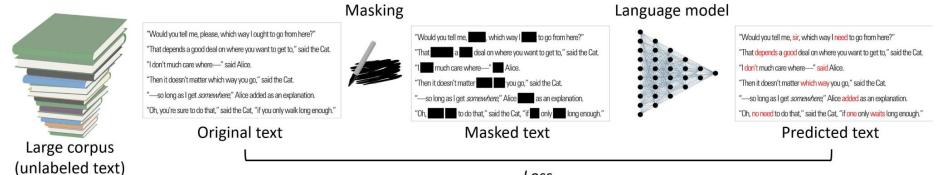


#### **Functional Annotation**

- Deep neural networks have already reached impressive results in protein three-dimensional structure prediction.
- ullet Here, we investigated if a such methodology could improve function annotation in  $\alpha\text{-Cyanobacteria}$

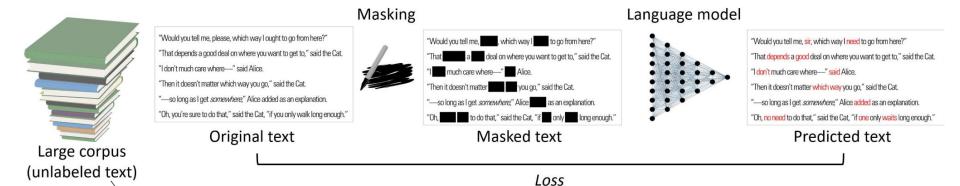


## Large language models

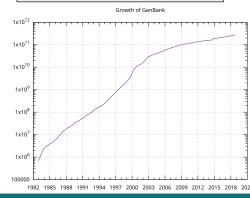


Loss

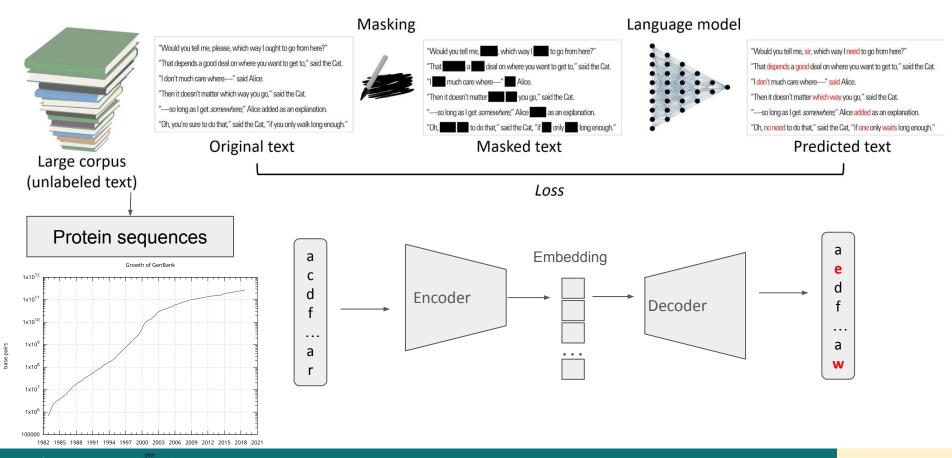
## **Protein large language models**



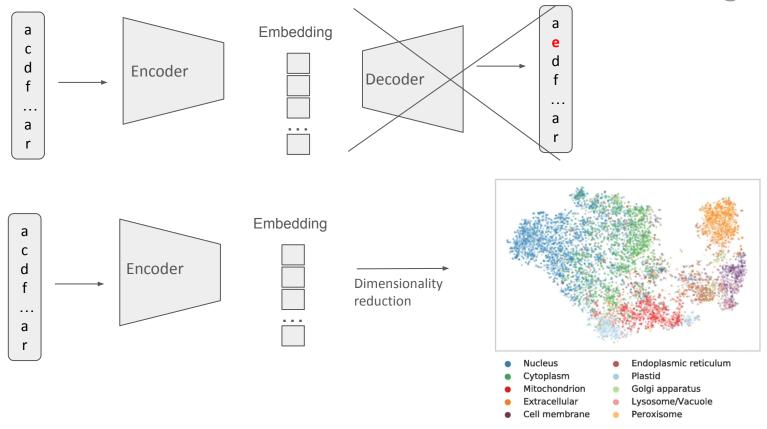
#### Protein sequences



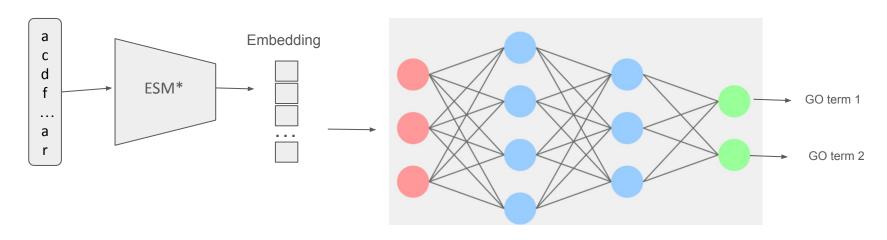
## **Protein language models**



# **Protein language models**



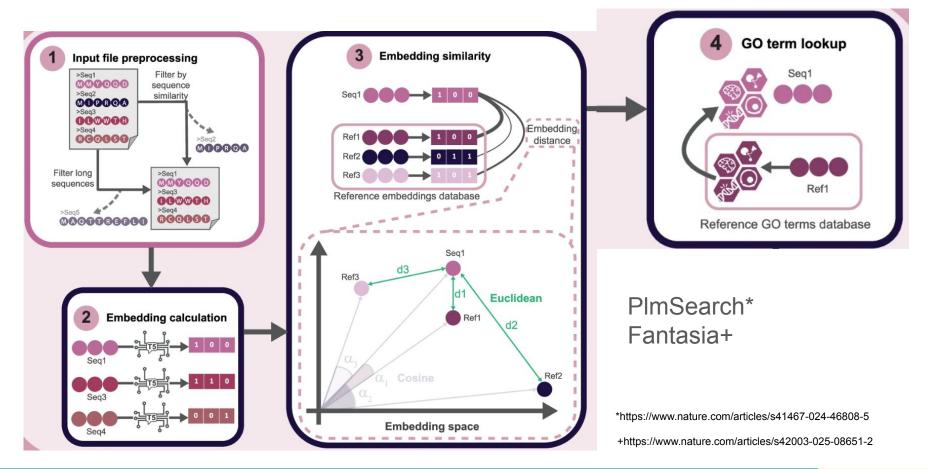
# **Functional Annotation with Deep-learning**



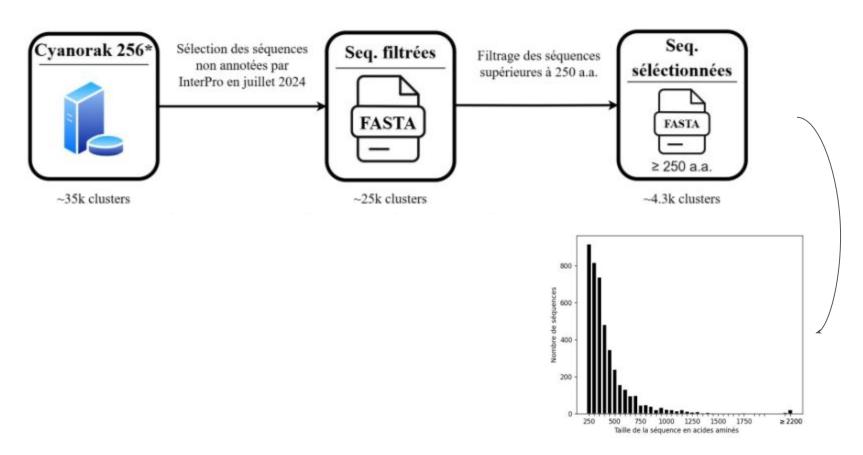
ML classifier

<sup>\*</sup>https://www.pnas.org/doi/abs/10.1073/pnas.2016239118

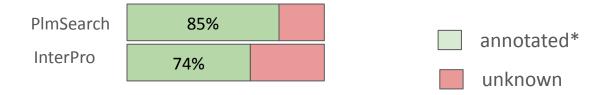
### **Functional Annotation with Deep-learning**

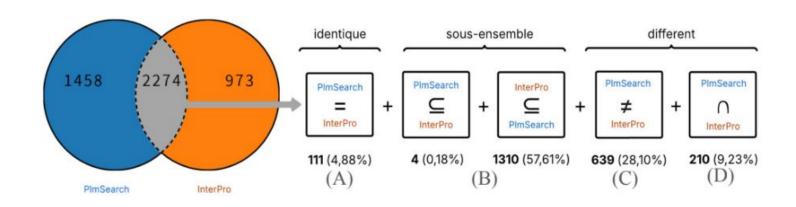


# **Data preparation**

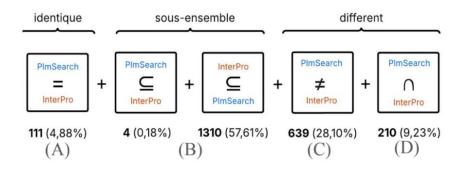


# **Results: comparing predictions**





# **Results: comparing predictions**



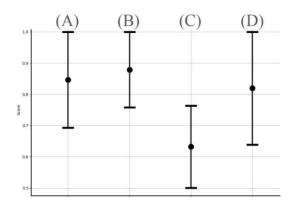


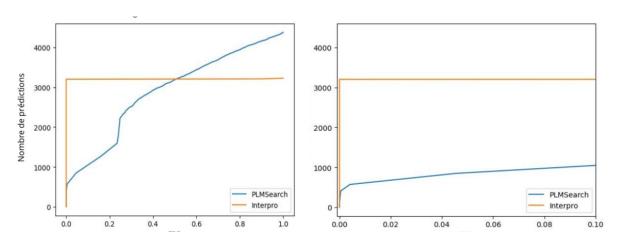
Tableau récapitulatif des tests statistiques de Mann-Whitney (ns : non significatif ; \*\*\* : < au risque  $\alpha$  = 1%)

TEST	P-VALUE	SIGNIFICATIVITÉ
A & B	0.556	ns
A & C	2.16 × 10 <sup>-27</sup>	***
A & D	4.28 × 10 <sup>-4</sup>	***
В & С	4.95 x 10 <sup>-140</sup>	***
B & D	1.78 × 10 <sup>-11</sup>	***
C & D	3.69 × 10 <sup>-27</sup>	***

## **Results : False discovery rates**

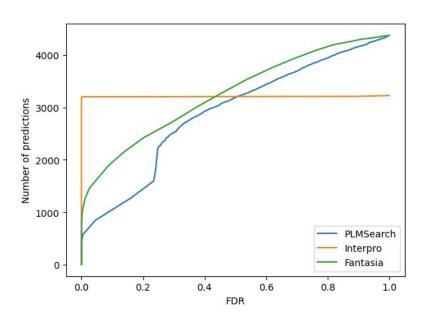
- We shuffled the amino acid order of each sequence with original dataset (D) to create an artificial database (R)
- FDR for a given score S is : number of predictions in R

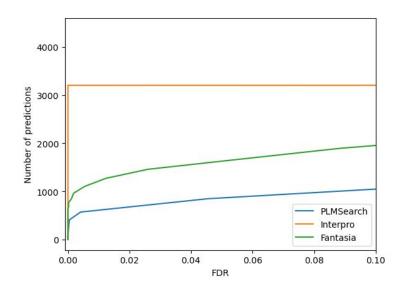
number of predictions in R + number of predictions in D



# **Results : False discovery rates**

We also tested Fantasia and measured FDR





#### Conclusion

- PLMSearch seems to complete/enrich the InterPro annotations.
- However, when it finds completely different annotations, the scores are significantly lower, indicating low accuracy.
- For a given FDR PLMSearch annotated less proteins than Interpro, the difference is even more evident for an FDR bounded to 10%.
- Higher FDR were also observed in Fantasia results.

## Acknowledges

- Emile Hembert L2 student Sorbonne Université
- Dorian Le Roux L2 student Sorbonne Université
- Fabio RJ Vieira IR Sorbonne Université
- Laurence Garczarek CNRS-DR
- Frédéric Partensky, CNRS-DR

Thanks for your attention!