RAPPPID: Improving Protein Interaction Prediction on Unseen Proteins

SCAN ME

Joseph Szymborski & Amin Emad

Intelligent Systems for Molecular Biology
2022 Madison, Wisconsin, USA

McGill

Emad's Computational Biology and Artificial Intelligence Lab

ISCB ISMB 2022 MADISON

Introduction

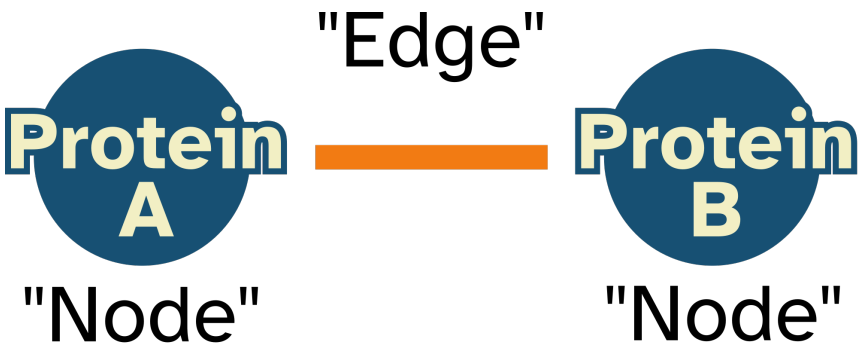
- Joseph Szymborski
  - McGill University,
    Department of Electrical & Computer Engineering
  - Mila, Quebec AI Institute
  - PhD Student in Amin Emad's COMBINE Lab

Emad's COMBINE Lab

Background: Protein-Protein Interactions

- Bio'l processes as an undirected graph of PPIs.

* An incomplete model,
but it's gotten us pretty far.



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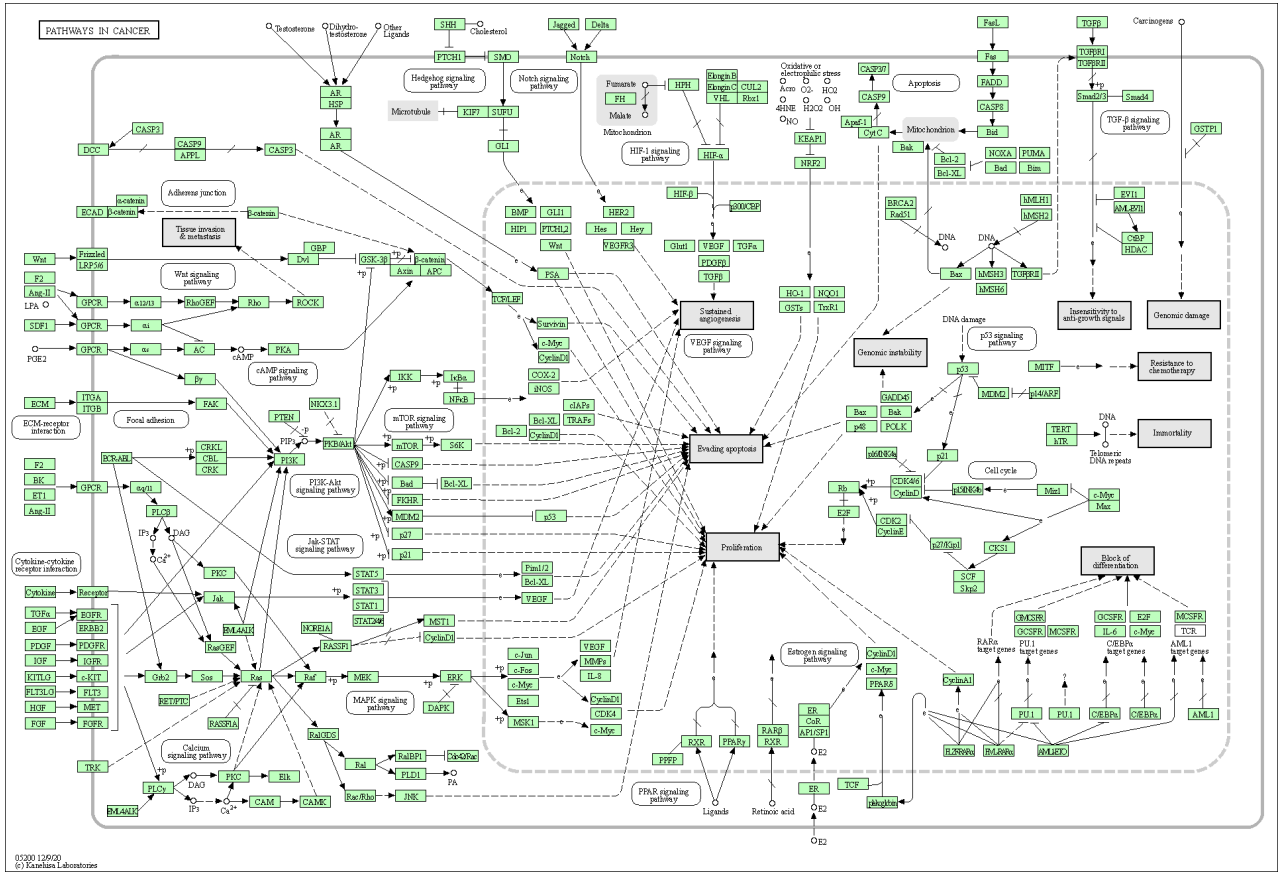
Background: Protein-Protein Interactions



See:
Kanehisa M. *et al.*
10.1093/nar/gkr988

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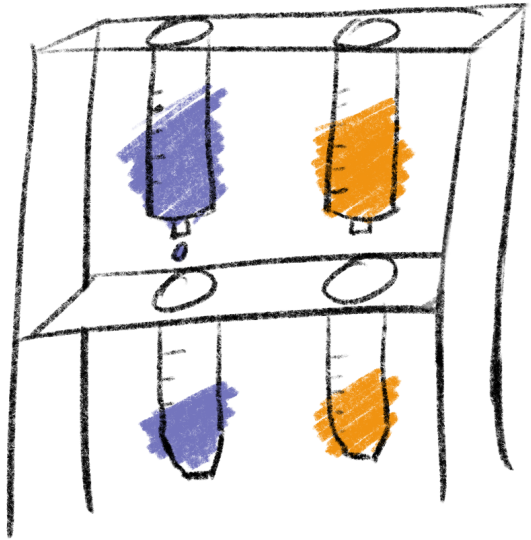
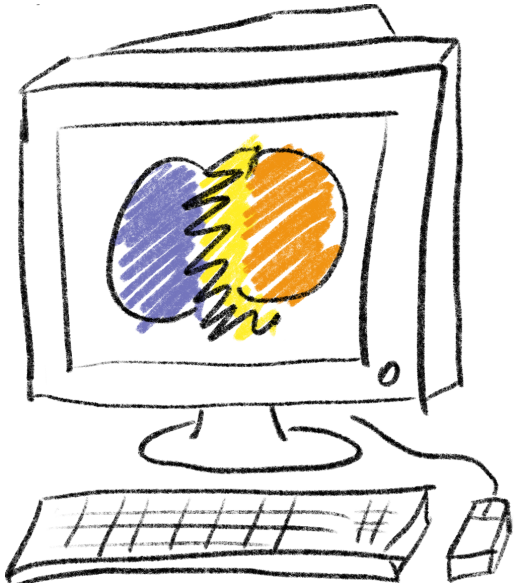
Background: Protein-Protein Interactions

- Protein interactions are typically identified through **“wet lab” experiments**.
- These experiments typically:
  - Take days/weeks.
  - Expensive reagents.
  - Often produce a lot of plastic waste.
  - Are quite definitive.



Background: Protein-Protein Interactions

- Predicting protein interactions using **computational models** try to address some of the **trade-offs of lab experiments**.
  - Take seconds/minutes.
  - Low-to-no cost.
  - Consume electricity and produces e-waste.
  - Not yet definitive.

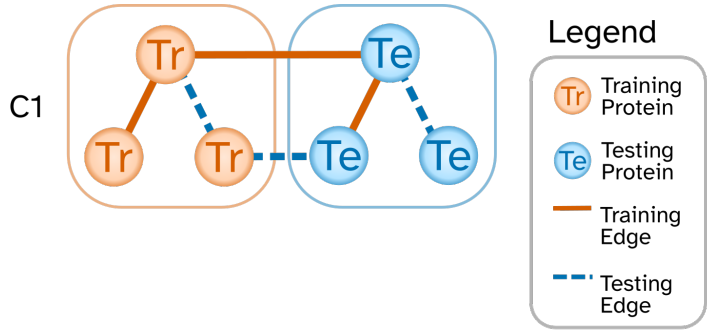


Background: Protein-Protein Interactions

Given two proteins, do they interact?

Background: Protein-Protein Interactions

AUROC on *H. sapiens*



Park, Y. & Marcotte, E. M. (2012).

Background: Protein-Protein Interactions

AUROC on *H. sapiens*

C1
0.81±0.01
0.85±0.01
0.64±0.01
0.77±0.01
0.81±0.01
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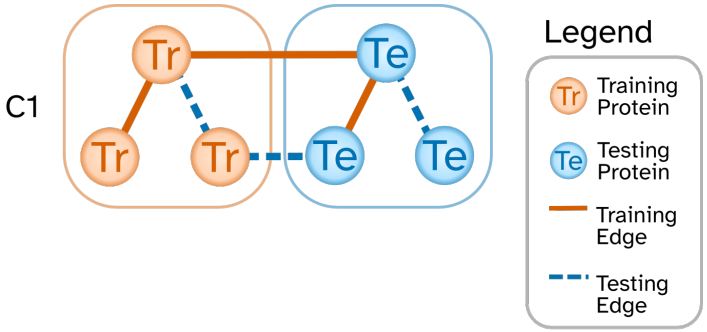
0.56±0.01



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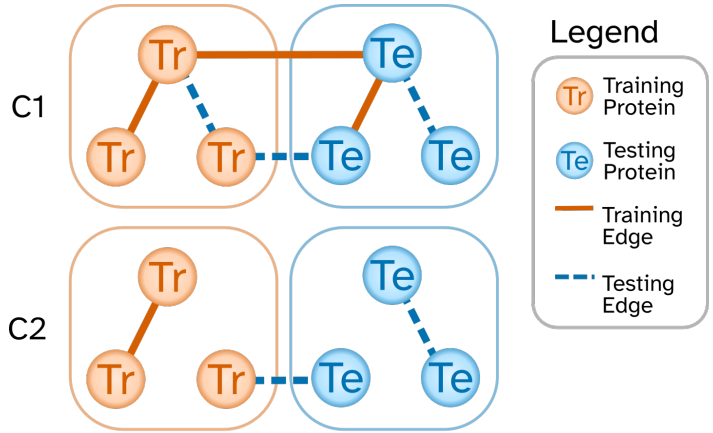
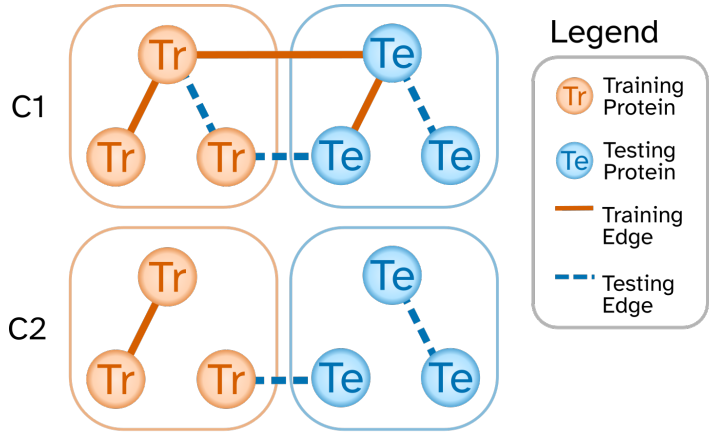


Park, Y. & Marcotte, E. M. (2012).

Background: Protein-Protein Interactions

AUROC on *H. sapiens*

C1	C2
0.81±0.01	0.61±0.01
0.85±0.01	0.60±0.01
0.64±0.01	0.55±0.01
0.77±0.01	0.57±0.02
0.81±0.01	0.59±0.01
0.77±0.01	0.64±0.01
0.56±0.01	0.53±0.01



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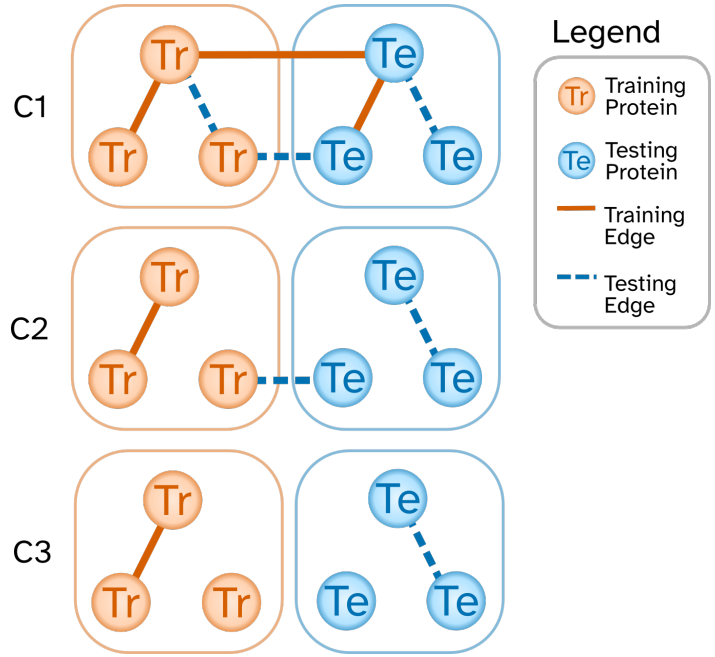

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Background: Protein-Protein Interactions

AUROC on *H. sapiens*

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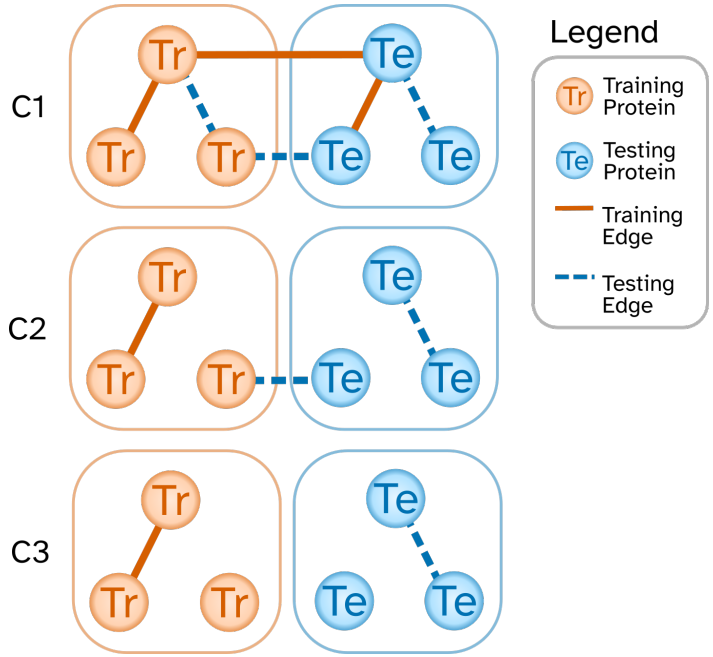
0.81±0.01	0.61±0.01	0.58±0.03
0.85±0.01	0.60±0.01	0.58±0.02
0.64±0.01	0.55±0.01	0.50±0.00
0.77±0.01	0.57±0.02	0.53±0.02
0.81±0.01	0.59±0.01	0.54±0.02
0.77±0.01	0.64±0.01	0.59±0.02
0.56±0.01	0.53±0.01	0.54±0.02



Park, Y. & Marcotte, E. M. (2012).

The Problem?

- It's hard to plug data leaks in PPI datasets.
- Many models depend on these leaks for their performance.
- How do we plug the leak?

Introducing 

Regularised **A**utomatic **P**rediction of **P**rotein-**P**rotein **I**nteractions using **D**eep Learning

Joseph Szymborski, Amin Emad, RAPPPID: Towards Generalisable Protein Interaction Prediction with AWD-LSTM Twin Networks, Bioinformatics, 2022; btac429, https://doi.org/10.1093/bioinformatics/btac429

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RAPPPID Architecture

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RAPPPID Architecture

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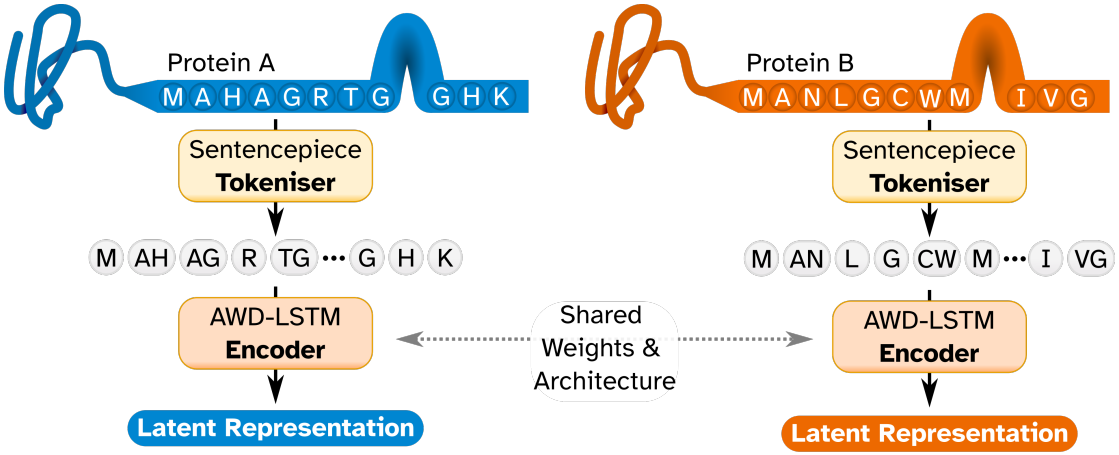
RAPPPID Architecture



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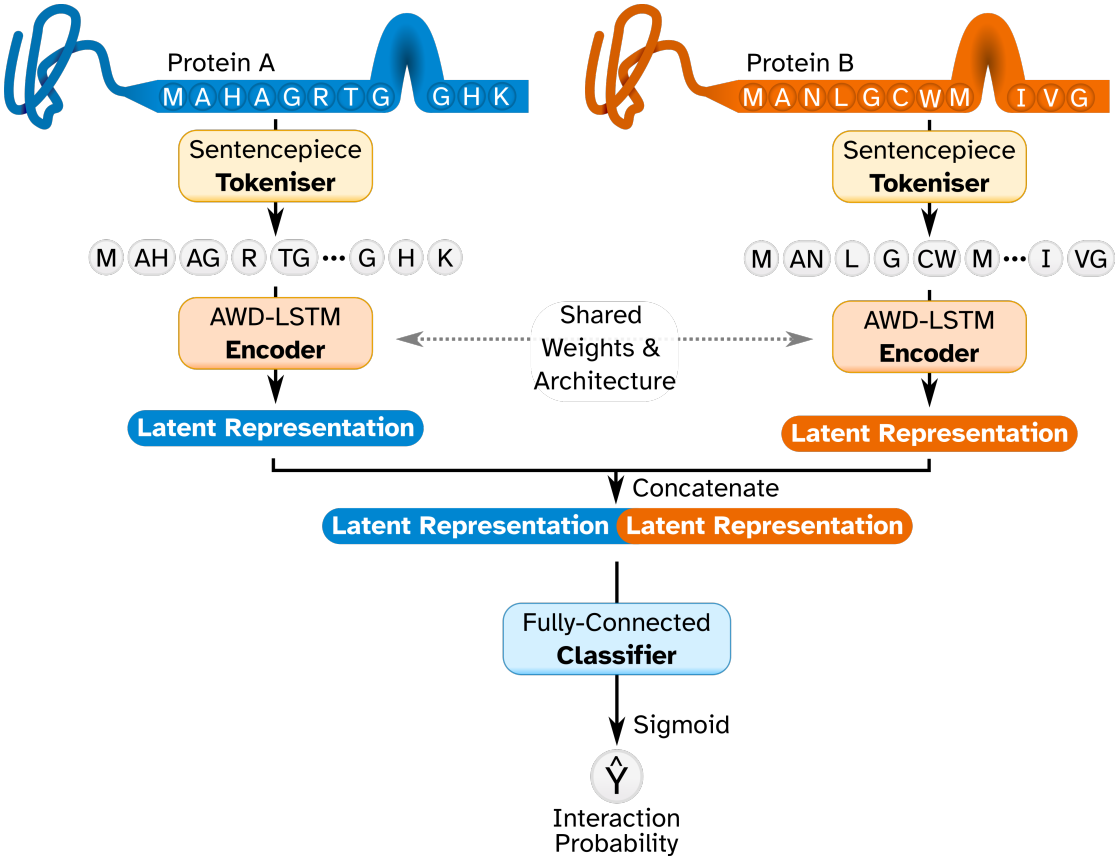
RAPPPID Architecture



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What makes RAPPPID different?

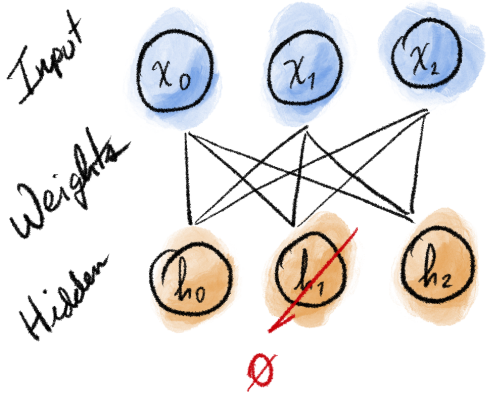
- In short, lots of regularisation
  - AWD-LSTM
  - Embedding dropout
  - Ranger21 Optimiser
  - Stochastic Weight Averaging (SWA)

What makes RAPPPID different?

- In short, lots of regularisation
  - AWD-LSTM
  - Embedding dropout
  - Ranger21 Optimiser
  - Stochastic Weight Averaging (SWA)
- Also
  - Sentencepiece tokenisation

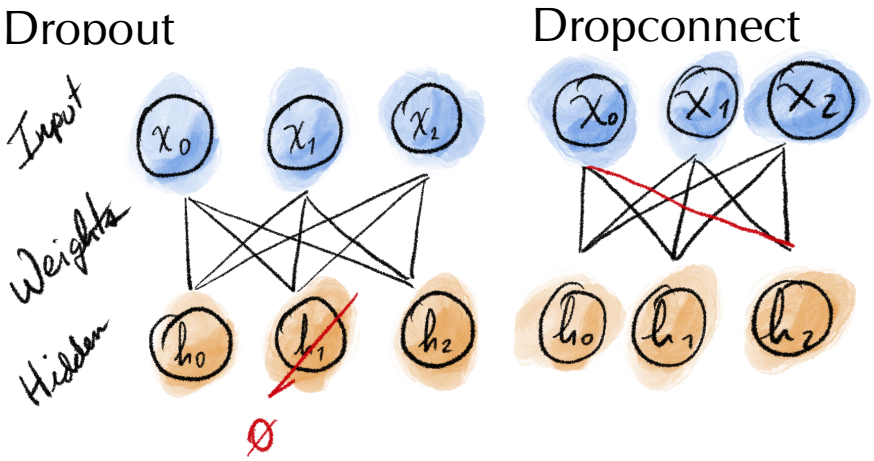
Regularising Recurrent Networks

Dropout



 Merity, S. *et al.* (2017)

Regularising Recurrent Networks



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Regularising Recurrent Networks

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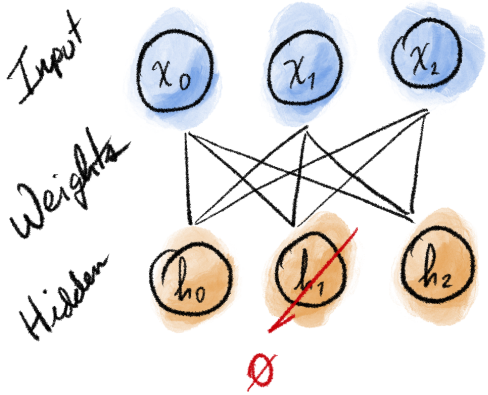
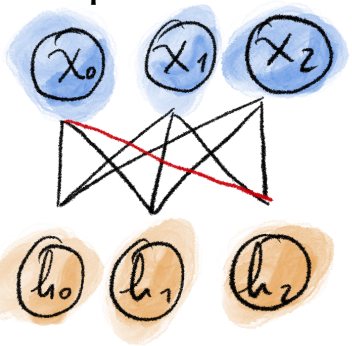


Dropconnect



Embedding Dropout

```
A   1 0 0 ... 0 0 0
C   0 1 0 ... 0 0 0
D   0 0 1 ... 0 0 0
.         .
.         .
.         .
V   0 0 0 ... 1 0 0
W   0 0 0 ... 0 1 0 › 0 0 0 ... 0 0 0
Y   0 0 0 ... 0 0 1
```

 Merity, S. *et al.* (2017)

Stochastic Weight Averaging (SWA)

- Very similar to Averaged Stochastic Gradient Descent but keeps a pair of weights:
  - One that the optimiser minimises (w).
  - Another that is a running average of the previous weight (w_{SWA}).

$$w_{SWA} \leftarrow \frac{w_{SWA} \cdot n_{models} + w}{n_{models} + 1}$$

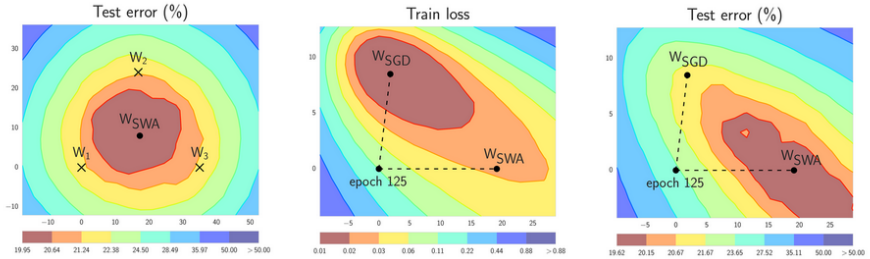
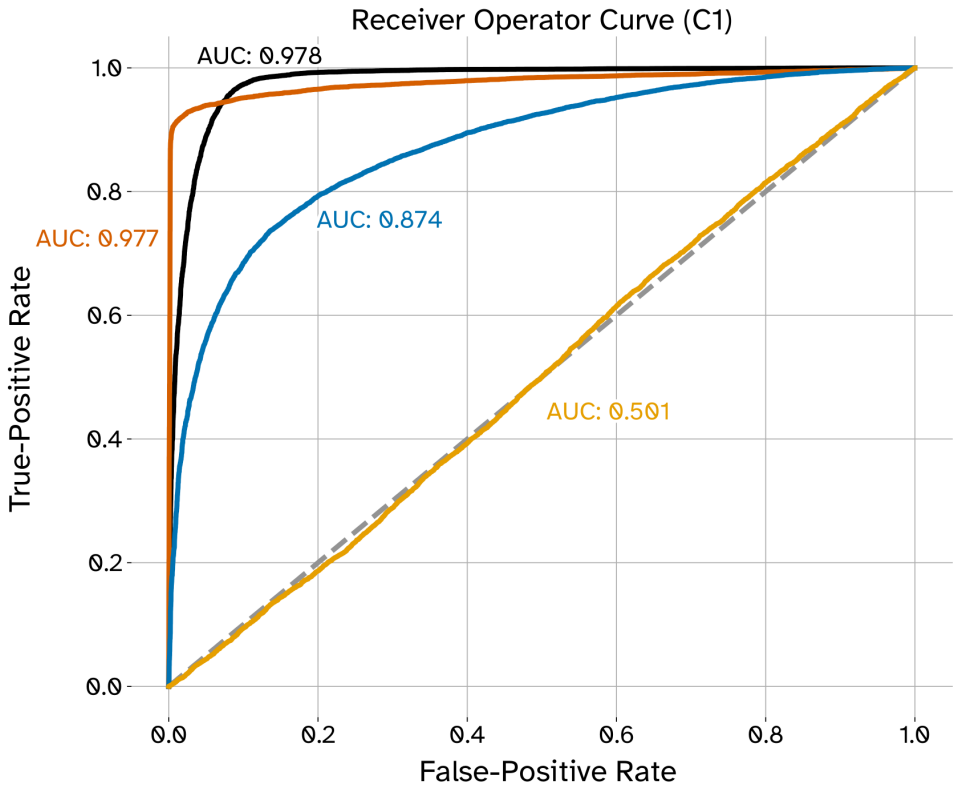
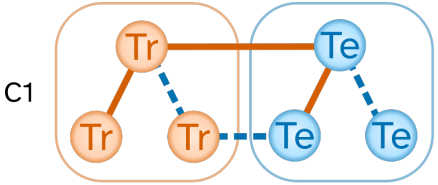
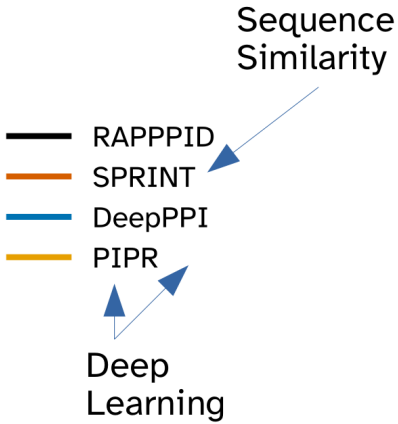


Figure 1. *Illustrations of SWA and SGD with a Preactivation ResNet-164 on CIFAR-100 [1]. **Left**: test error surface for three FGE samples and the corresponding SWA solution (averaging in weight space). **Middle** and **Right**: test error and train loss surfaces showing the weights proposed by SGD (at convergence) and SWA, starting from the same initialization of SGD after 125 training epochs. Please see [1] for details on how these figures were constructed.*

How does RAPPPID perform?







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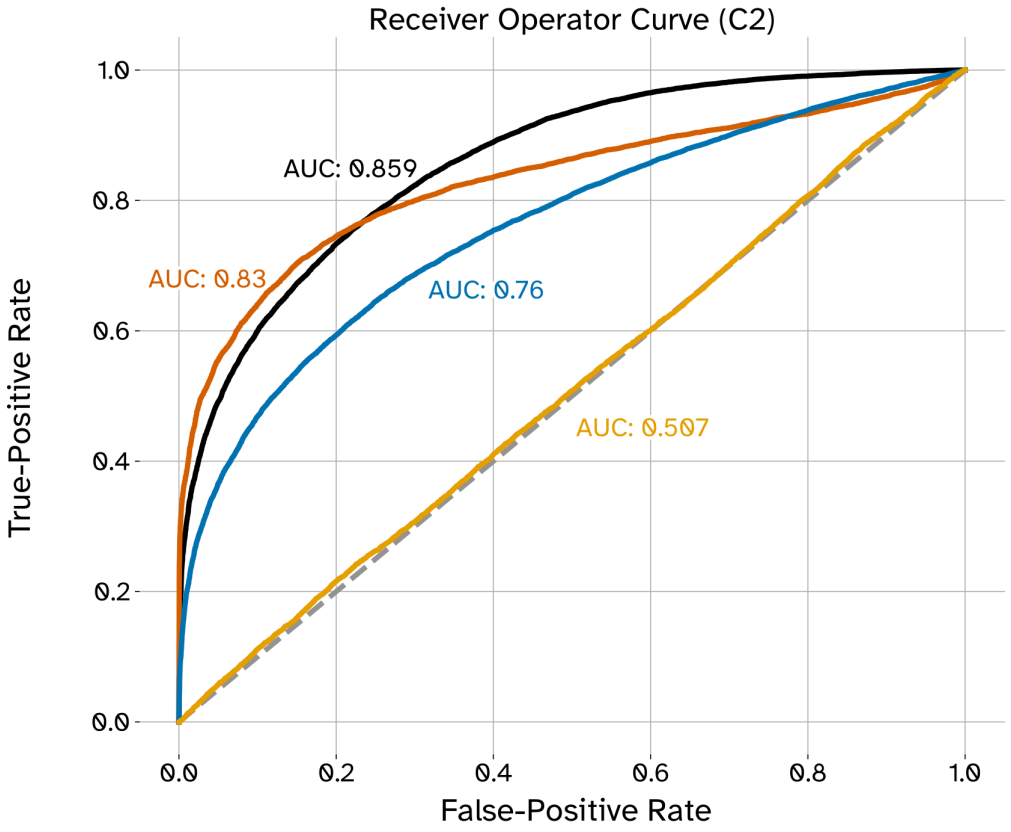

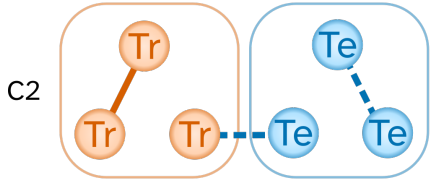

Sequence Similarity

RAPPPID
SPRINT
DeepPPI
PIPR

Deep Learning

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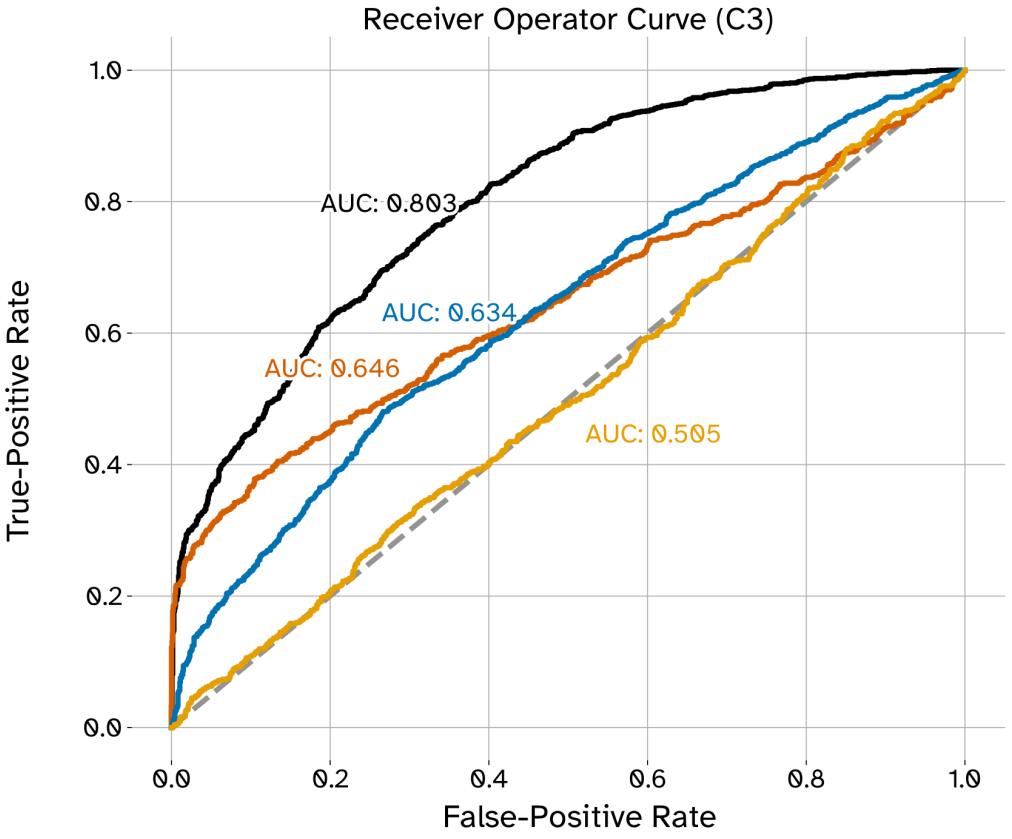
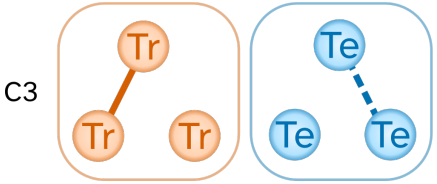
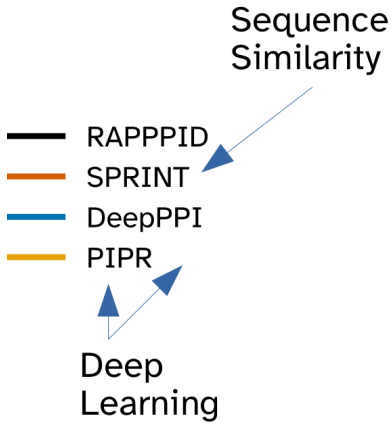
How does RAPPPID perform?







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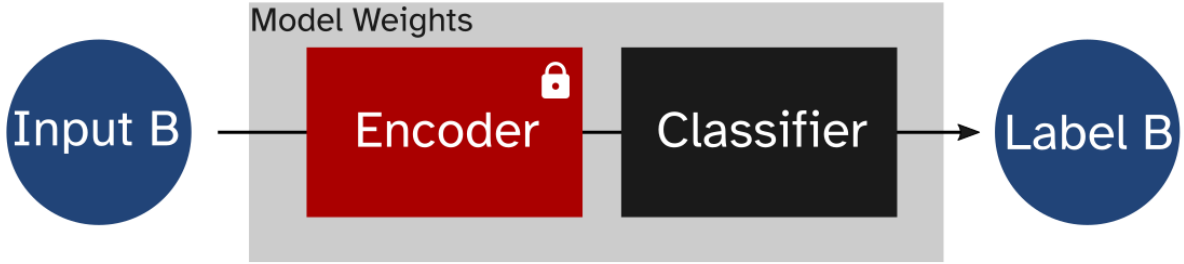
RAPPPID performance vs. data providence

Results from an ablation study conducted on RAPPPID. Each model is trained/tested twice on three randomly generated C3 datasets. The performance metrics correspond to held-out test sets.

	RAPPPID (original)	RAPPPID -SWA	RAPPPID + Adam	RAPPPID- AWD	RAPPPID- SentencePiece	RAPPPID + TransfLG	RAPPPID + TransfSM
Test AUROC	0.792 (±0.007)	0.782 (±0.007)	0.791 (±0.025)	0.762 (±0.020)	0.749 (±0.009)	0.670 (±0.030)	0.747 (±0.026)
AUROC Diff	N/A	-1.20%	-0.100%	-3.70%	-5.37%	-15.3%	-5.68%
Test APR	0.794 (±0.009)	0.783 (±0.007)	0.792 (±0.032)	0.757 (±0.022)	0.748 (±0.011)	0.686 (±0.040)	0.758 (±0.025)
APR Diff	N/A	-1.37%	-0.273%	-4.62%	-5.85%	-13.6%	-4.61%

Transfer Learning on X-Ray Crystallography Data

- BioLIP dataset: semi-curated dataset of Protein/Ligand interactions based on the PDB
- We pretrain on STRINGDB, then fine-tune on BioLIP

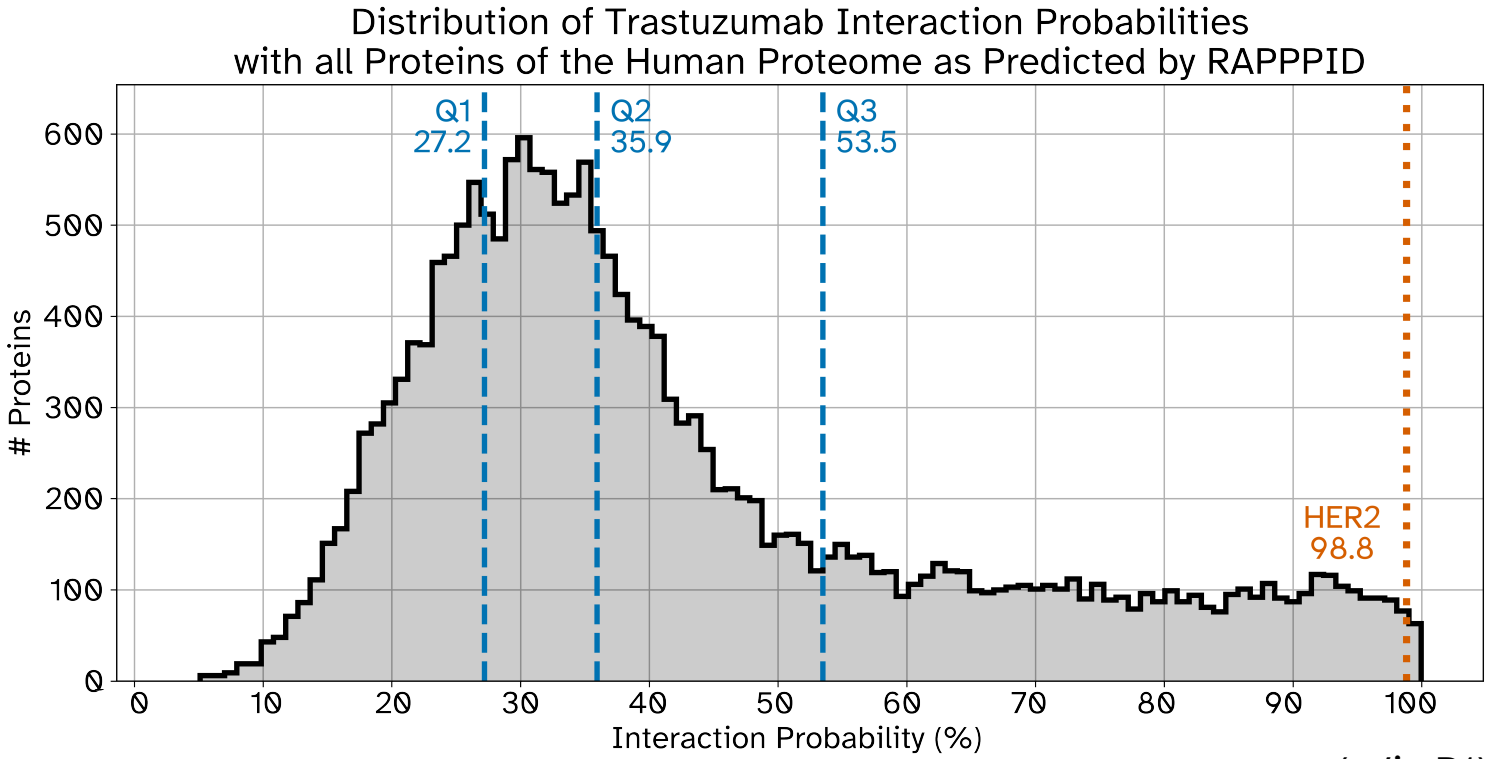


- Training on STRING DB, fine-tuning on BioLIP, and testing on BioLIP:
  - AUROC of **0.909**

RAPPPID predicts interaction of HER2 with Trastuzumab and Pertuzumab

- How might one use RAPPPID to validate hypothesized interactions between:
  - Target proteins
  - Candidate therapeutic proteins and peptides
- Two examples: Trastuzumab and Pertuzumab.
  - Recombinant humanised monoclonal antibodies
  - Used for HER2-positive metastatic breast cancer

RAPPPID predicts interaction of HER2 with Trastuzumab and Pertuzumab



(w/in P1)

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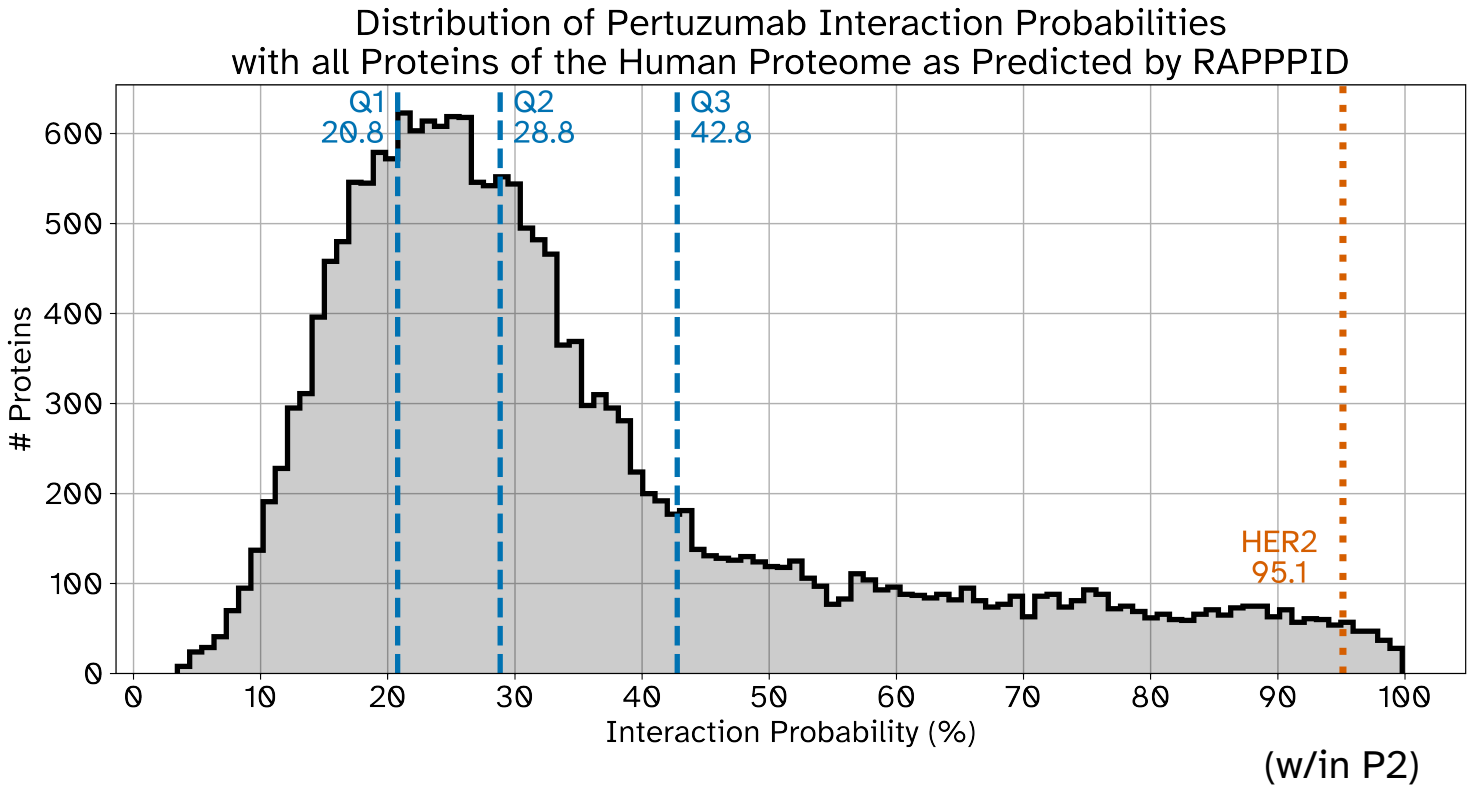
RAPPPID predicts interaction of HER2 with Trastuzumab and Pertuzumab



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Acknowledgements

- Thanks to the members of the COMBINE lab for their feedback and support
  - P.D.F: Antoine Soulé
  - Ph.D.: David E. Hostallero, Ali Saberi, Yitian Zhang
  - M.Sc.: Mohamed Reda El Khili, Jessica (Yihui) Li, Chen Su, Abulrahman Takiddeen

Thanks to our supporters:

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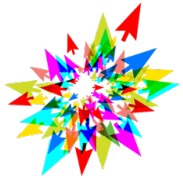


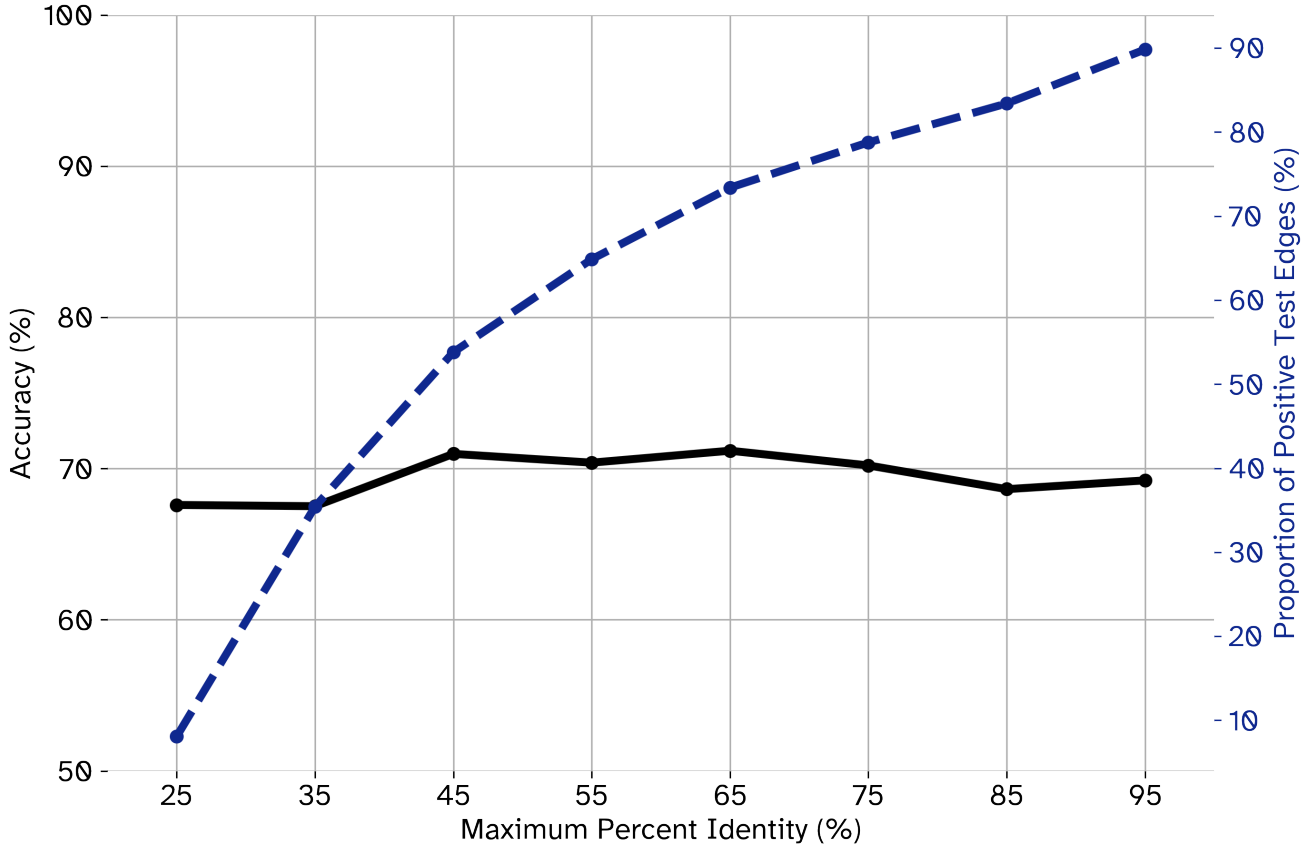
compute canada | calcul canada

Calcul Québec

Thank you

Questions?

Is RAPPPID just identifying similar sequences?



A1

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Existing PPI datasets are not great for Deep Learning.

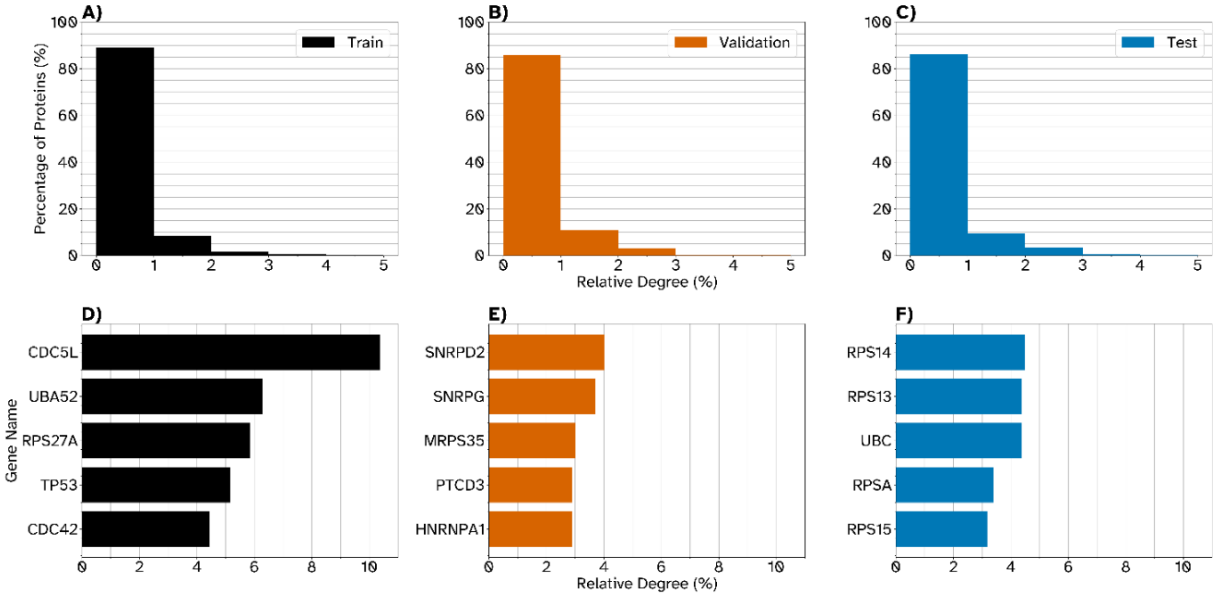
- We wanted to use additional datasets, like HIPPIE and iRefWeb
- Only STRING has enough high-confidence edges for deep learning purposes
  - 98.5% fewer edges in HIPPIE than in STRING (human, 95% confidence)
  - 87.9% fewer edges with an 85% confidence.
  - 75% fewer edges in iRefWeb than in STRING (human, 95% confidence)
- This is made worse by the fact that PPI datasets overfit terribly to begin with

False-Positive Rate

- We evaluated the false-positive rate of confidence score-filtered STRING dataset
  - We used curated and experimentally validated non-interacting protein pairs from **Negatome**
- We compared the set of proteins that are:
  - Both in STRING and Negatome
  - Evaluating the number of negative edges in Negatome that were considered a positive edge in this interesection
- Estimated the false-positive rate of our STRING dataset to be **4.01%**
- Falls within the extected **5%** upper-bound given by our 95% confidence threshold

Protein Over-Representation

- PPI graphs are understood to be scale-free in the general case
- That means that some hub proteins might be over-represented
- But that isn't the case.



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Curated negative examples

- We investigated using the curated database “Negatome” for the negative samples
- There are too few (1,191 negative *H. sapiens* pairs; 263,130 positive pairs)

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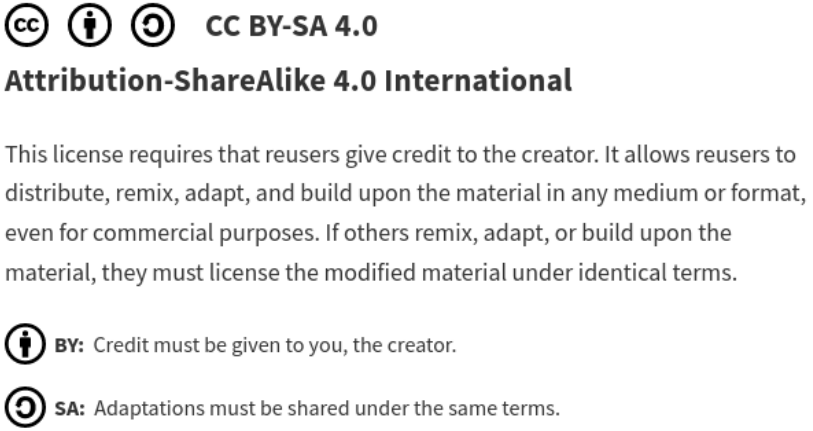

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