

Learning Sparse and Structured Gaussian Embedding of protein sequences using pairwise constraints

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Introduction

- What do they have in common?
 - Basic biology to keep them alive and functioning.
- E.g. Undergoing several different biochemical processes such as:
 - Breaking down food
 - Repairing tissues or worn out cells
 - Replicating DNA





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Proteins

- Proteins allow organisms to undergo these basic life processes
- Need energy from your last food?
 - Proteins build the enzymes used by the digestive system to break down and extract nutrients from food.
- Want to build muscles?
 - Muscles are build from proteins.
- How can organism stay alive?
 - Proteins form the enzymes need to replicate DNA and replace old and worn out cells.





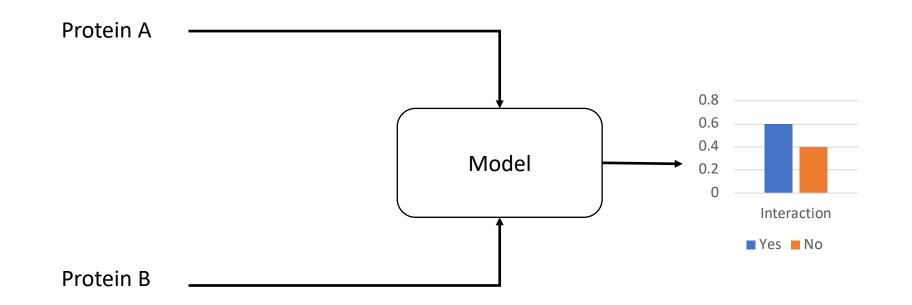
Protein-Protein interactions (PPI)

- Proteins rarely act alone as their functions tend to be regulated
- Numerous proteins organized by their physical contacts forms molecular machines that carries out biological and molecular processes
- Study of these contacts:
 - Understand biological phenomenon
 - Insights about molecular etiology of diseases
 - Discovery of putative drug targets
- Contacts between proteins: Protein Protein interactions (PPI)



Problem

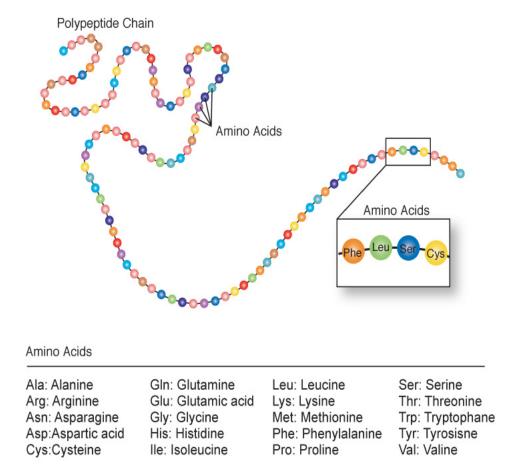
Predict if two proteins interact.



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Amino acid sequence

- Proteins are made up of smaller units called amino acids.
- Strings of amino acids are arranged in particular order.
 - Protein A5Z2X5 MRPAQLLLNTAKKTSGGYKIPVELTPLFLAVGVALCSGTYFT YKKLRTDETLRLTGNPEL SSLDEVLAKDKD
- Amino acid sequence is the primary structure of the protein.
 - determines the protein's unique three-dimensional shape.



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rarediseases.info.nih.gov/GlossaryDescription/14/0



Previous works

- Predict interactions between a pair of protein sequences
- State-of-the-art methods proposed Siamese network to model the mutual influence between proteins.

DPPI (Hashemifar et al. 2018)

- Deep convolutional neural network (CNN) to learn protein representation
- Doesn't consider sequential information of amino acids

PIPR (Chen et al. 2019)

 Deep Recurrent Convolutional neural network (RCNN) to learn protein representation





Challenges

- Hard to explain the predictions i.e. lack transparency
- Computationally expensive approach in Siamese setting

For instance:

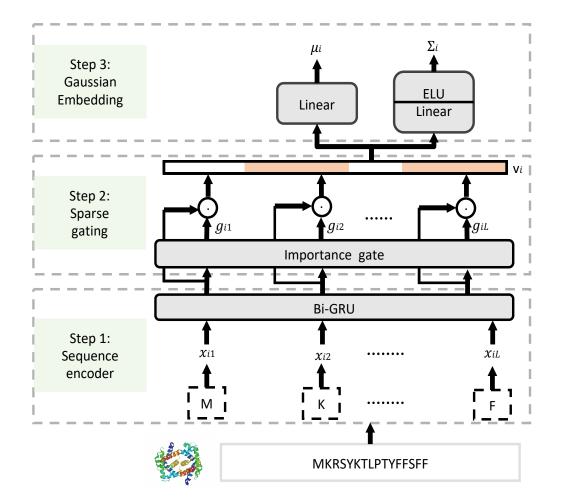
- Human has nearly 20,000 proteins.
- Nearly 200 million possible interactions.
- If processing an interaction takes 1 second, total processing time > 6 years.

Proposed approach

- Sequence encoder
 - Bidirectional GRU to model contextual and sequential properties of amino acids
 - Handles variable length sequences
 - Captures long term dependencies
- Sparse gating

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- Guides model to selectively focus on specific amino acids in the sequence
- Gaussian embedding
 - Model the uncertainty about the representation of amino acid sequences



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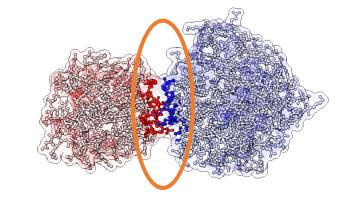
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Sparse gating mechanism

 Proteins interact via interface, small region of protein structure



<u>Softmax</u>	<u>Sparsemax¹</u>	<u>Fusedmax²</u>
Full support	Sparse weight but distributed	Sparse and contiguous



1. From Softmax to Sparsemax: A Sparse Model of Attention and Multi-Label Classification, André F. T. Martins, Ramón Fernandez Astudillo, ICML 2016. 2. A Regularized Framework for Sparse and Structured Neural Attention, Niculae, Vlad, and Mathieu Blondel, NeurIPS 2017.



Experimental setup

- Select a batch of n protein sequences
- Encode these sequences to Gaussian distributions
- Retrieve positive and negative interactions that involve these n proteins
- Minimize the statistical distance between interacting proteins while maximizing the distance for noninteracting proteins.

$$dist^{2} = ||\mu_{i} - \mu_{j}||_{2}^{2} + ||\Sigma_{i}^{\frac{1}{2}} - \Sigma_{j}^{\frac{1}{2}}||_{F}^{2}$$
$$\mathcal{L} = \sum_{i} \sum_{(i,j)\in\mathbf{Y}^{+}} \sum_{(i,k)\in\mathbf{Y}^{-}} (E_{ij}^{2} + \exp(-E_{ik}))$$



Results

Mathad	Yeast		Human	
Method	AUROC	AP	AUROC	AP
Our method + sparsemax	0.924±0.002	0.925±0.001	0.887±0.003	0.891±0.002
Our method + fusedmax	$0.919 {\pm} 0.003$	$0.921 {\pm} 0.002$	$0.881 {\pm} 0.002$	$0.886 {\pm} 0.001$
DPPI (Hashemifar et al. 2018)	$0.891 {\pm} 0.004$	$0.857 {\pm} 0.007$	$0.870 {\pm} 0.004$	$0.835 {\pm} 0.005$
PIPR (Chen et al. 2019)	$0.909 {\pm} 0.003$	$0.912{\pm}0.004$	$0.878 {\pm} 0.002$	$0.882{\pm}0.003$

Table 1: Comparison with the state-of-the-art models





Ablation study

Model configuration		AUROC	AP
No gating		$0.880{\pm}0.001$	$0.875 {\pm} 0.003$
SE + RF	Softmax	$\overline{0.881}\pm\overline{0.001}$	$\bar{0.877}\pm\bar{0.001}$
	Fusedmax	$0.909 {\pm} 0.001$	$0.912{\pm}0.002$
	Sparsemax	$0.913 {\pm} 0.001$	$0.916 {\pm} 0.002$
GE + RF	Softmax	$\bar{0.882}\pm\bar{0.001}$	$\bar{0}.\bar{8}7\bar{9}\pm\bar{0}.\bar{0}0\bar{2}$
	Fusedmax	$0.919 {\pm} 0.003$	$0.921 {\pm} 0.001$
	Sparsemax	$0.924{\pm}0.002$	$0.925{\pm}0.001$

Table 2: Study of model components on Yeast dataset





Interpretability

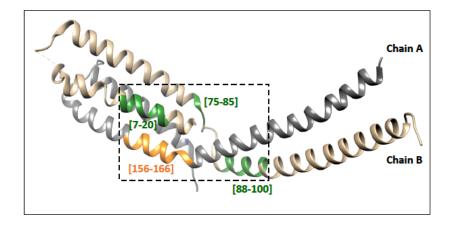
	Ground truth motif	Sparsemax	Fusedmax
LSM8	MSATLKDYLNKRVVIIKVDG	MSATLKDYLNKRVVIIKVDG	MSATLKDYLNKRVVIIKVDG
	ECLIASLNGFDKNTNLFITN	ECLIASLNGFDKNTNLFITN	ECLIASLNGFDKNTNLFITN
	VFNRISKEFICKAQLLRGSE	VFNRISKEFICKAQLLRGSE	VFNRISKEFICKAQLLRGSE
	IALVGLIDAENDDSLAPIDE	IALVGLIDAENDDSLAPIDE	IALVGLIDAENDDSLAPIDE
	KKVPMLKDTKNKIENEHVIW	KKVPMLKDTKNKIENEHVIW	KKVPMLKDTKNKIENEHVIW
	EKVYESKTK	EKVYESKTK	EKVYESKTK
SMD2	MSSQIIDRPKHELSRAELEE	MSSQIIDRPKHELSRAELEE	MSSQIIDRPKHELSRAELEE
	LEEFEFKHGPMSLI <mark>NDAMVT</mark>	LEEFEFKHGPMSLINDAMVT	LEEFEFKHGPMSLINDAMVT
	RTPVIISLRNNHKIIARVKA	RTPVIISLRNNHKIIARVKA	RTPVIISLRNNHKIIARVKA
	FDRHCNMVLENVKELWTEKK	FDRHCNMVLENVKELWTEKK	FDRHCNMVLENVKELWTEKK
	GKNVINRERFISKLFLRGDS	GKNVINRERFISKLFLRGDS	GKNVINRERFISKLFLRGDS
	VIVVLKTPVE	VIVVLKTPVE	VIVVLKTPVE
RPC10	MPPLPQNYAQQQP <mark>SNWDKFK</mark>	MPPLPQNYAQQQPSNWDKFK	MPPLPQNYAQQQPSNWDKFK
	MGLMMGTTVGVCTGILFGGF	MGLMMGTTVGVCTGILFGGF	MGLMMGTTVGVCTGILFGGF
	AIATQGPGPDGVVRTLGKYI	AIATQGPGPDGVVRTLGKYI	AIATQGPGPDGVVRTLGKYI
	AGSAGTFGLFMSIGSIIRS	AGSAGTFGLFMSIGSIIRSD	AGSAGTFGLFMSIGSIIRSD
	SESSPMSHPNLNLQQQARLE	SESSPMSHPNLNLQQQARLE	SESSPMSHPNLNLQQQARLE
	MWKLRAKYGIRKD	MWKLRAKYGIRKD	MWKLRAKYGIRKD
MGR2	M <u>LSFCPSCNNMLLITSGDSG</u>	MLSFCPSCNNMLLITSGDSG	MLSFCPSCNNMLLITSGDSG
	VYTLACRSCPYEFPIEGIEI	VYTLACRSCPYEFPIEGIEI	VYTLACRSCPYEFPIEGIEI
	YDRKKLPRKEVDDVLGGGWD	YDRKKLPRKEVDDVLGGGWD	YDRKKLPRKEVDDVLGGGWD
	NVDQTK <mark>TQCPNYDTCGGESA</mark>	NVDQTKTQCPNYDTCGGESA	NVDQTKTQCPNYDTCGGESA
	YFFQLQIRSADEPMTTFYKC	YFFQLQIRSADEPMTTFYKC	YFFQLQIRSADEPMTTFYKC
	VNCGHRWKEN	VNCGHRWKEN	VNCGHRWKEN

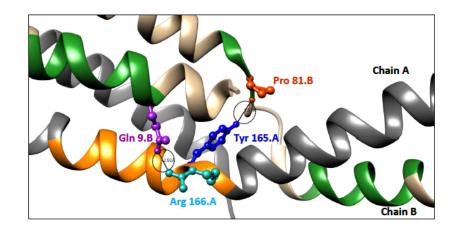


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Interpretability: case study





(a) Important segments predicted by our model. (b) Validated contact between the residues in the predicted segments.



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