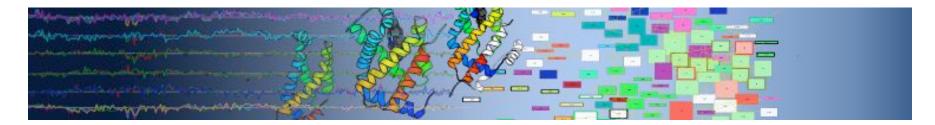
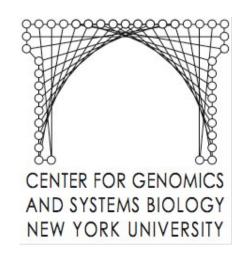
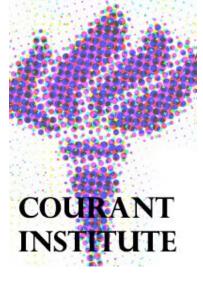
## PROTEIN FUNCTION PREDICTION USING STRUCTURAL HOMOLOGY

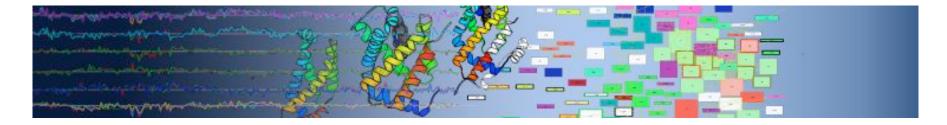


### KEVIN DREW,

Lars Malmstroem, Glenn Butterfoss, Richard Bonneau







## Genome Annotation using Homology

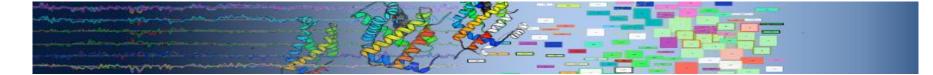
Sequence Homology 40%-60% Coverage Score = 107 bits (264), Expect = 6e-23 Identities = 63/160 (39%), Positives = 97/160 (60%), Gaps = 7/160 (4%) Query:1 MSVMYKKILYPTDFSETAEIALKHVKTLKAEEVILLDEREIKKRDIFSLLLGVA 60 M M++K+L+PTDFSE A A++ + ++ EVILLDE +++ L+ G + Sbjct:1 MIFMFRKVLFPTDFSEGAYRAVEVFEKMEVGEVILLDEGTLEE-----LMDGYS 55 ...

### Structural Homology:





### Function Annotations



# Structural Homology: Example

Bacteriocin AS-48, Casp 4

### 1E68

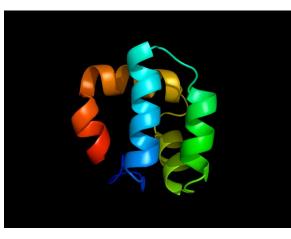
### Sequence:

MAKEFGIPAAVAGTVLNVVEAGGW VTTIVSILTAVGSGGLSLLAAAGRES IKAYLKKEIKKKGKRAVIAW

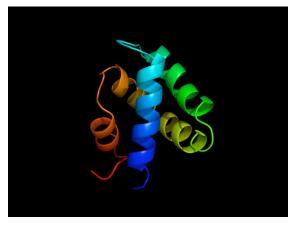
GYFCESCRKIIQKLEDMVGPQPNEDTVTQAAS QVCDKLKILRGLCKKIMRSFLRRISWDILTGKKP QAICVDIKICKE

1NKL

Structure:

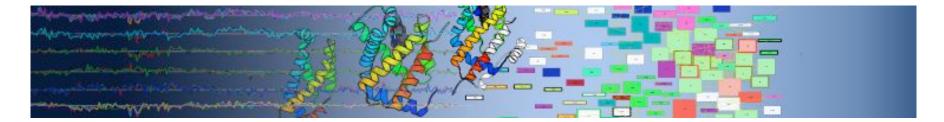


4%=

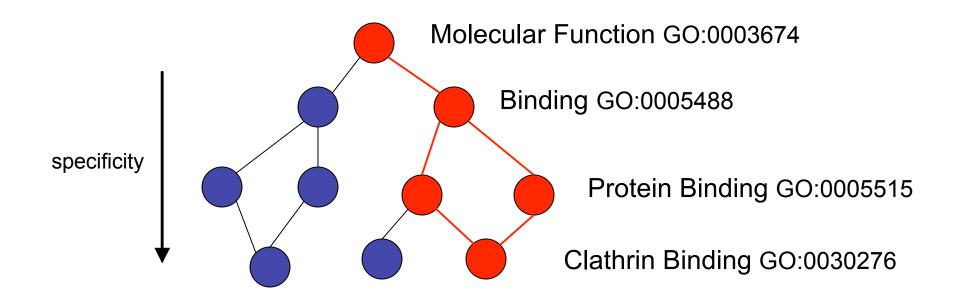


Function: Cyclic Bacterial Lysin = NK Lysin <sub>3</sub>

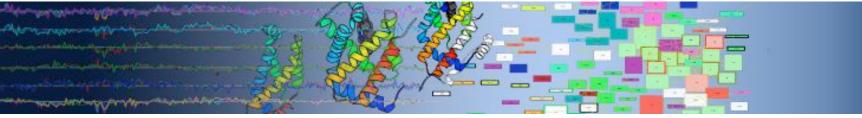
Bonneau, R., Tsai, J., Ruczinski, I., Baker, D. Functional Inferences from Blind ab Initio Protein Structure Predictions. J. Structural Biology. (2001)



## Gene Ontology (GO)

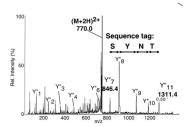


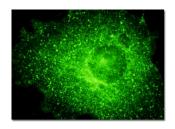
Molecular Function GO Graph



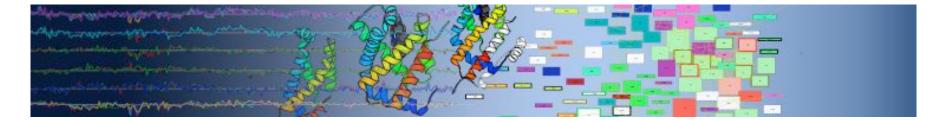
## Additional Evidence of Function for Integration with Structure

- GO Biological Process
- GO Cellular Component
- Experimental Data
  - Mass Spec Pull Down
  - Fluorescent Localization

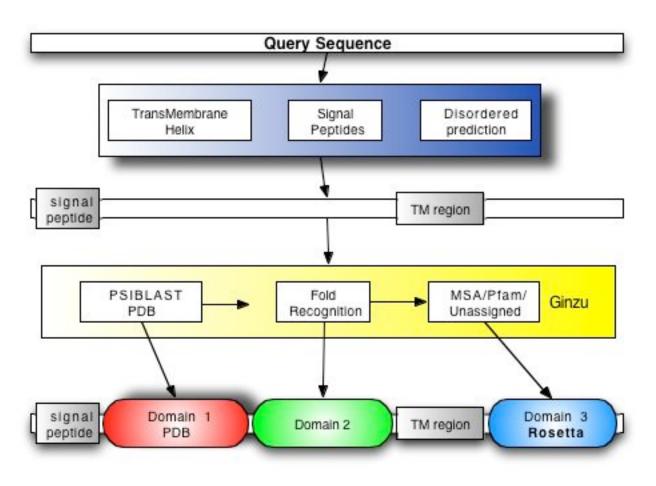


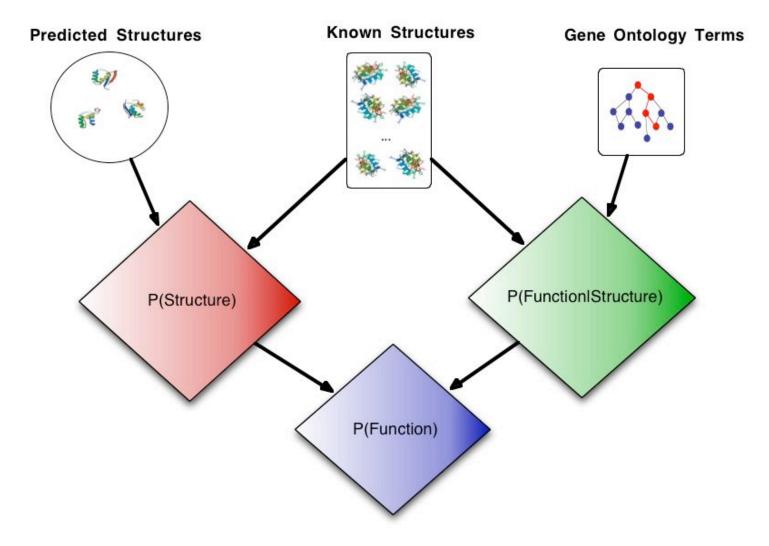


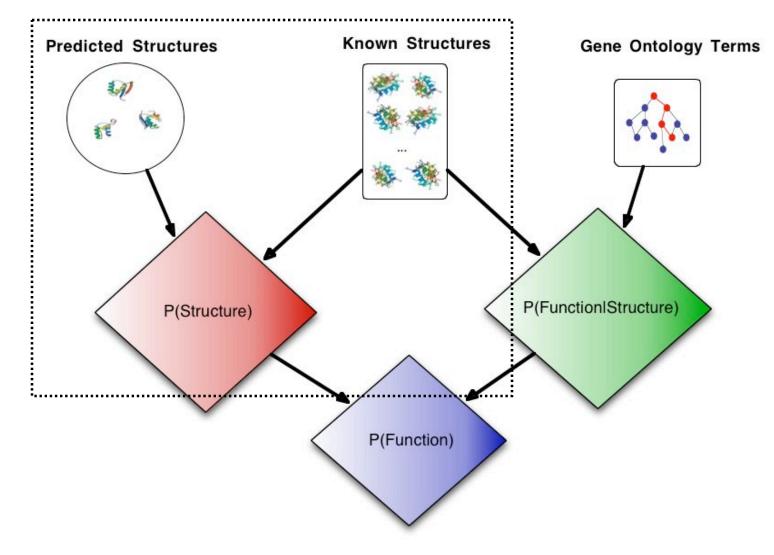
Generally boosts confidence of predictions

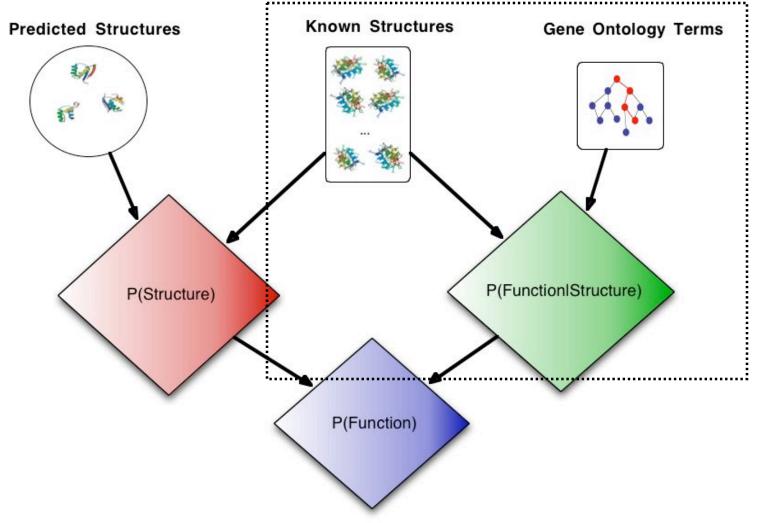


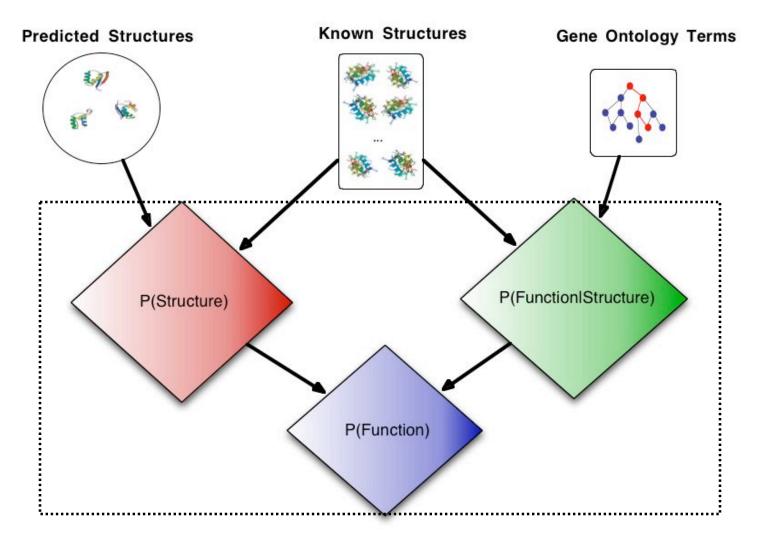
## **Protein Domain Prediction**

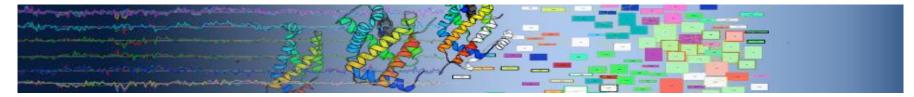




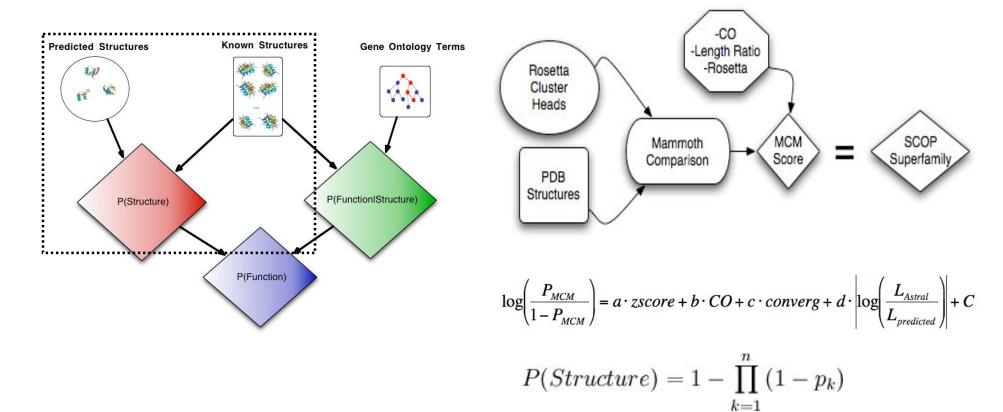


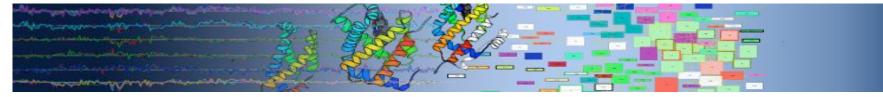




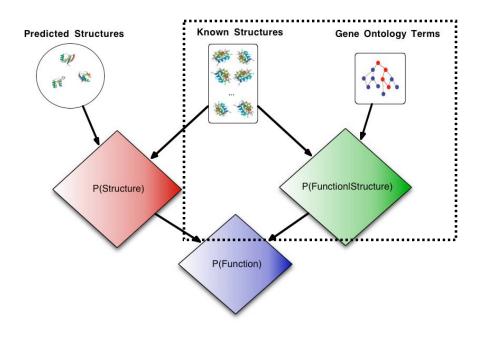


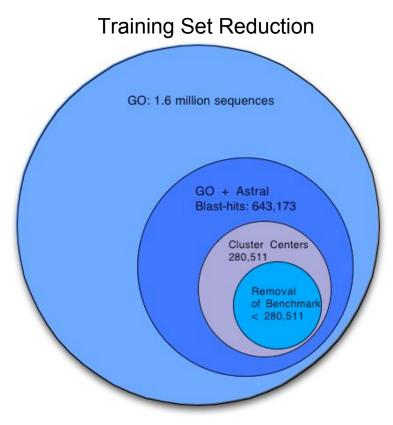
## Matching Predicted Structures to Known Structures

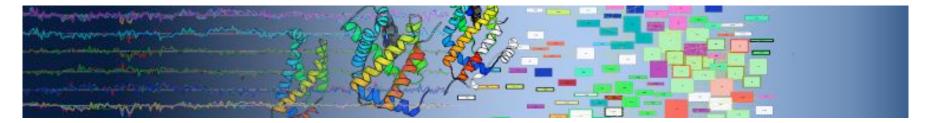




## Training Data Derived from GO and Known Structures



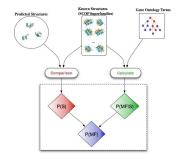


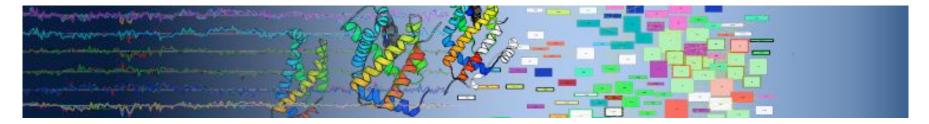


## Naïve Bayes

- In words: what is the probability of a variable, y, is true given features, x, over the probability y is false given the features x.
  - Take the log and if its >0 its more likely to be true than false.
- y = molecular function and **x** = {sf, bp, cc}

$$LL_X = log\left(\frac{P(y = TRUE)}{P(y = FALSE)}\right) + \sum_{j=1}^d log\left(\frac{P(x_j|y = TRUE)}{P(x_j|y = FALSE)}\right)$$

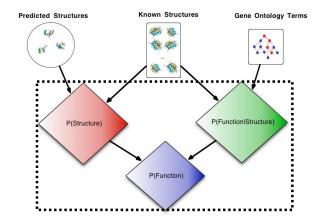


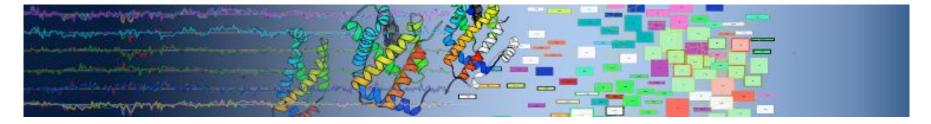


$$LL_X = log\Big(\frac{P(y = TRUE)}{P(y = FALSE)}\Big) + \sum_{j=1}^d log\Big(\frac{P(x_j|y = TRUE)}{P(x_j|y = FALSE)}\Big)$$

Naive Bayes

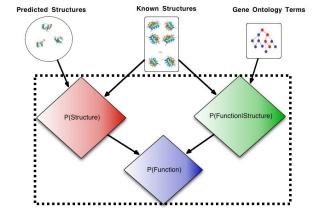
$$LL_{PLS} = log\left(\frac{P(Function)}{P(Function)}\right) + \sum_{i=1}^{N} \left[P(Structure_i) * log\left(\frac{P(Structure_i|Function)}{P(Structure_i|Function)}\right)\right] + \sum_{j=P,L} log\left(\frac{P(x_j|Function)}{P(x_j|Function)}\right) = \frac{1}{2} \left[P(Structure_i) * log\left(\frac{P(Structure_i|Function)}{P(Structure_i|Function)}\right)\right] + \sum_{j=P,L} log\left(\frac{P(x_j|Function)}{P(x_j|Function)}\right) = \frac{1}{2} \left[P(Structure_i) * log\left(\frac{P(Structure_i|Function)}{P(Structure_i|Function)}\right)\right] + \sum_{j=P,L} log\left(\frac{P(x_j|Function)}{P(Structure_i|Function)}\right) = \frac{1}{2} \left[P(Structure_i) * log\left(\frac{P(Structure_i|Function)}{P(Structure_i|Function)}\right)\right] + \sum_{j=P,L} log\left(\frac{P(x_j|Function)}{P(Structure_i|Function)}\right) = \frac{1}{2} \left[P(Structure_i) * log\left(\frac{P(Structure_i|Function)}{P(Structure_i|Function)}\right)\right] + \sum_{j=P,L} log\left(\frac{P(x_j|Function)}{P(Structure_i|Function)}\right) = \frac{1}{2} \left[P(Structure_i) * log\left(\frac{P(Structure_i|Function)}{P(Structure_i|Function)}\right)\right] + \sum_{j=P,L} log\left(\frac{P(Structure_i|Function)}{P(Structure_i|Function)}\right) = \frac{1}{2} \left[P(Structure_i) * log\left(\frac{P(Structure_i|Function)}{P(Structure_i|Function)}\right)\right] + \sum_{j=P,L} log\left(\frac{P(Structure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Functure_i|Func$$



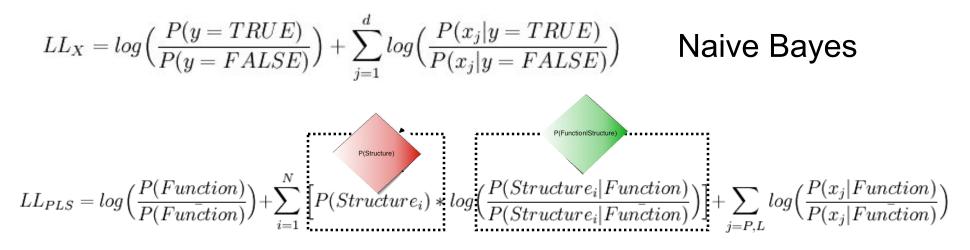


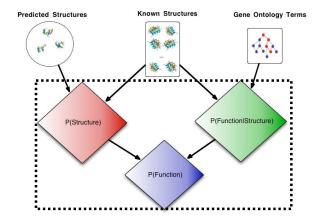
$$LL_X = log\Big(\frac{P(y = TRUE)}{P(y = FALSE)}\Big) + \sum_{j=1}^d log\Big(\frac{P(x_j|y = TRUE)}{P(x_j|y = FALSE)}\Big)$$
 Naive Bayes

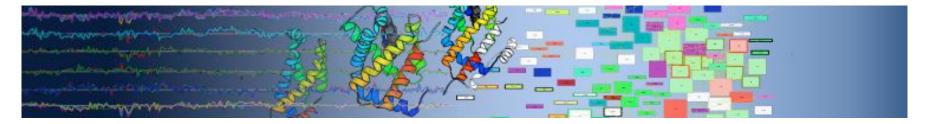
$$LL_{PLS} = log\left(\frac{P(Function)}{P(Function)}\right) + \sum_{i=1}^{N} \left[P(Structure_i) * log\left(\frac{P(Structure_i|Function)}{P(Structure_i|Function)}\right)\right] + \sum_{j=P,L} log\left(\frac{P(x_j|Function)}{P(x_j|Function)}\right)$$





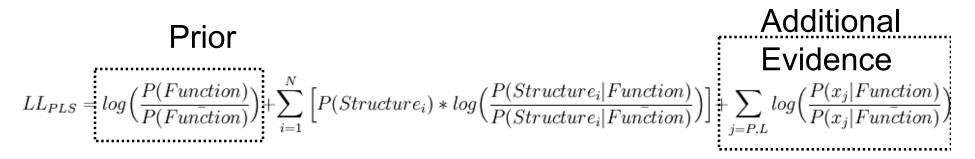


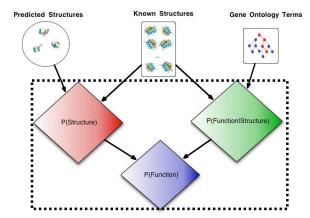


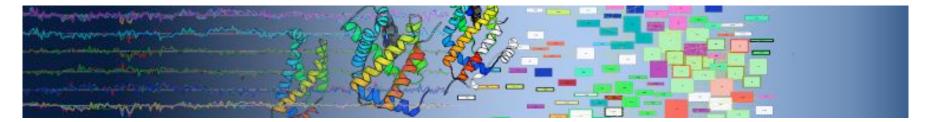


$$LL_X = log\left(\frac{P(y = TRUE)}{P(y = FALSE)}\right) + \sum_{j=1}^d log\left(\frac{P(x_j|y = TRUE)}{P(x_j|y = FALSE)}\right)$$

**Naive Bayes** 



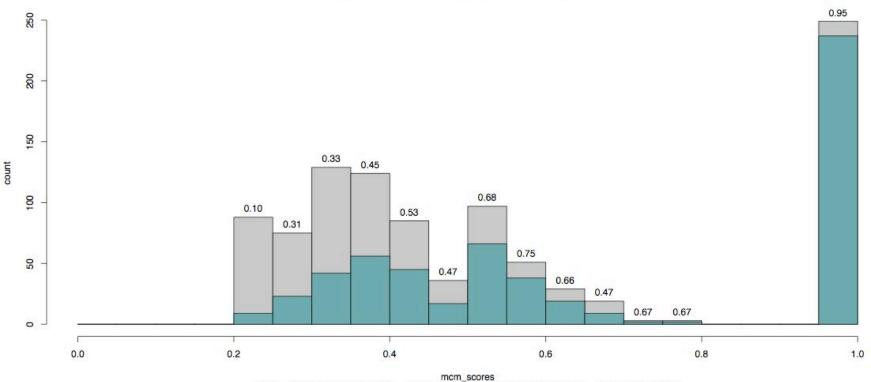




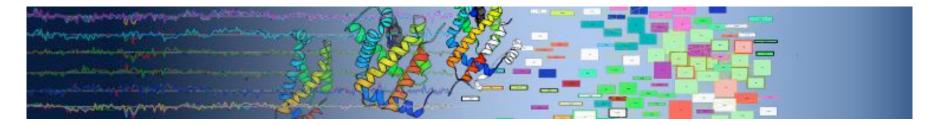
## **Results:** Solved Structures

How accurate are we when we predict SCOP Superfamily for PDB Structures?

histogram of scop\_benchmark : 565 true / 988 total

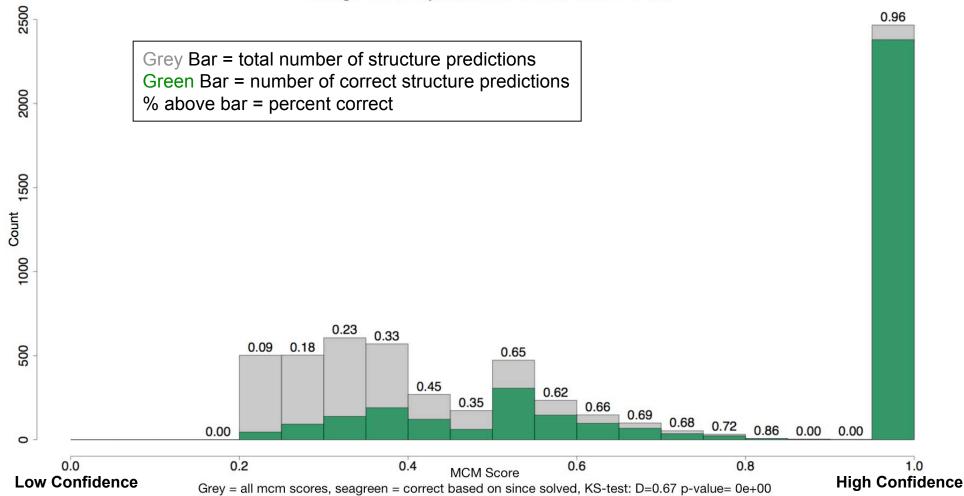


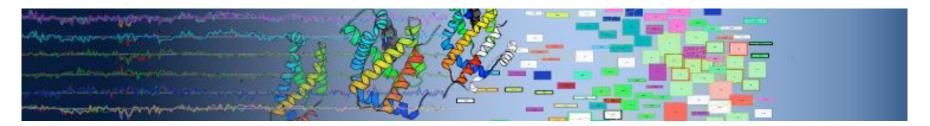
grey = all mcm scores, cadetblue = correct based on since solved, KS-test: D= 0.5 p-value= 0e+00



#### How accurate are we when we predict Structure for Swissprot Proteins?

Histogram of swissprot\_benchmark : 3709 true / 6143 total



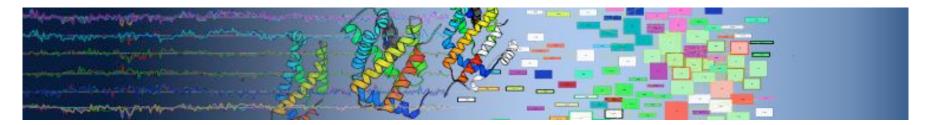


How do we measure preformance of function predictions?

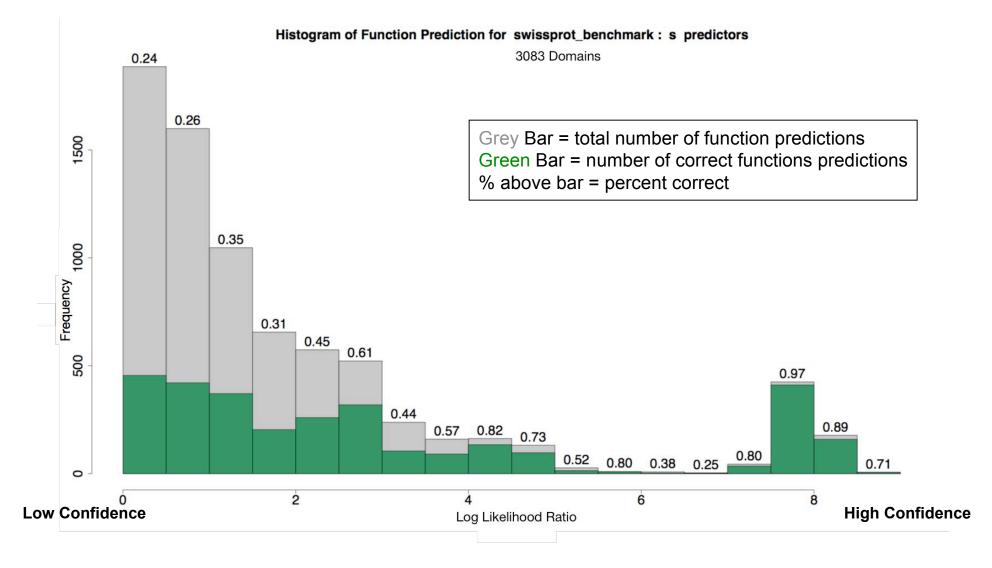
Accuracy - # of Correct / # of Total

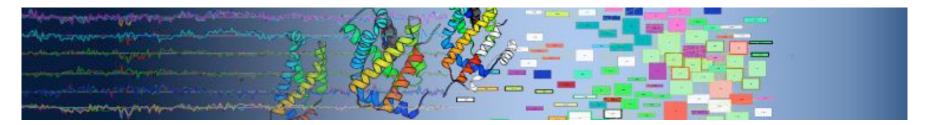
Coverage - # of Proteins with High Confidence Predictions

Specificity and Uniqueness - # of proteins with annotations (background probability)

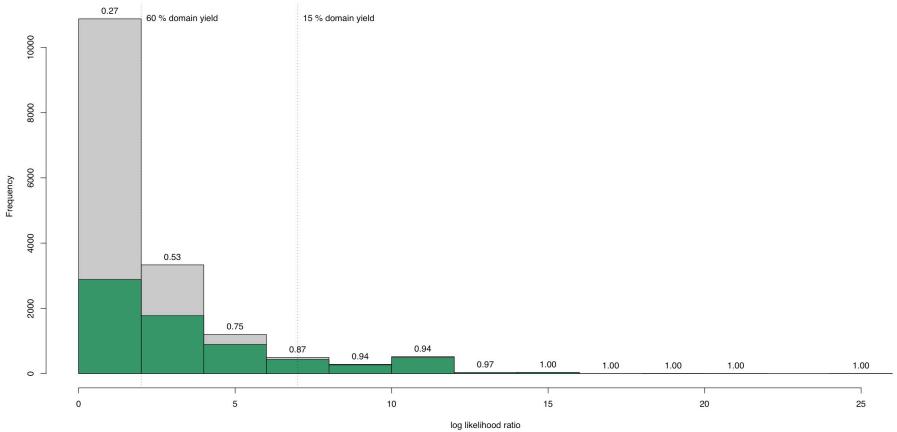


### How accurate are our function predictions using structure only?



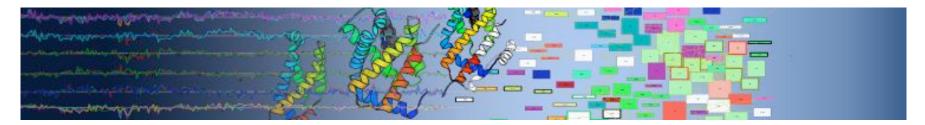


#### How accurate are our function predictions using GO process & structure?

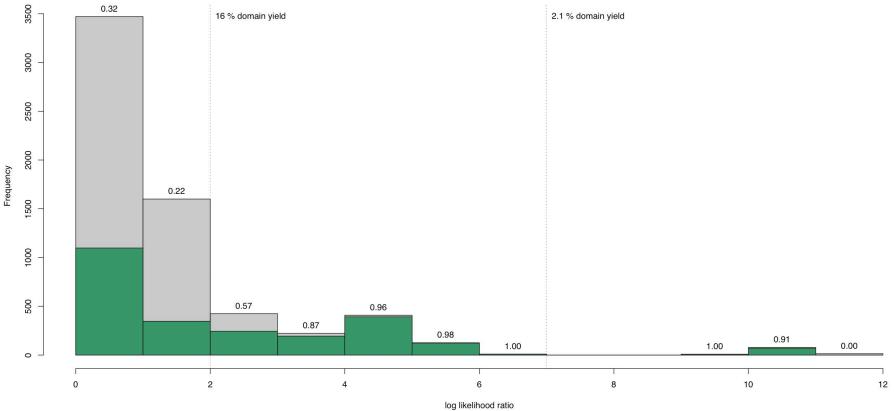


#### Histogram of Function Prediction for swissprot\_benchmark : ps predictors

domains: 3083

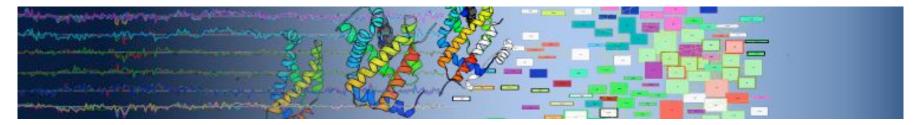


### What does structure provide over GO process alone?

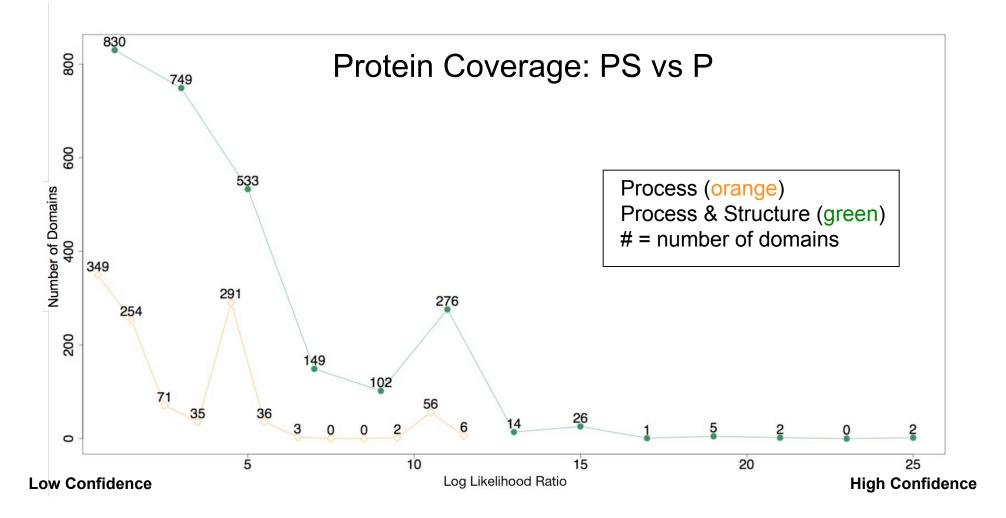


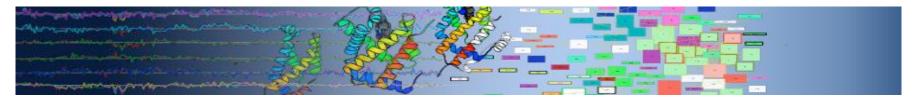
Histogram of Function Prediction for swissprot\_benchmark : p predictors

domains: 3083



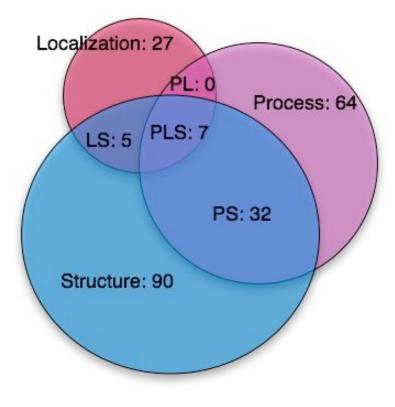
### What does structure provide over GO process alone?





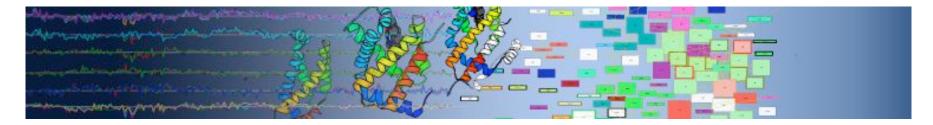
### Uniqueness and Specificity of GO Functions

#### **Unique Functions by Evidence**



### Sampling of Predicted Terms

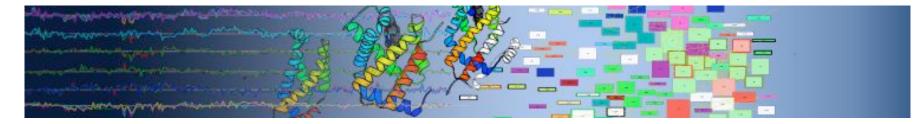
GO ID		Percent of Genes with Terms
GO:0005198	structural molecule activity	0.03
GO:0003735	structural constituent of ribosome	0.02
GO:0003676	nucleic acid binding	0.17
GO:0003723	RNA binding	0.04
GO:0016491	oxidoreductase activity	0.16
GO:0046872	metal ion binding	0.11
GO:0016787	hydrolase activity	0.24
GO:0043167	ion binding	0.12
GO:0043169	cation binding	0.11
GO:0005509	calcium ion binding	0.01
	••	•
GO:0004550	nucleoside diphosphate kinase ad	ctivity 0.0009
GO:0005496	steroid binding	0.001
GO:0042379	chemokine receptor binding	0.0006
GO:0030234	enzyme regulator activity	0.01
GO:0016788	hydrolase activity, acting on ester	bonds 0.04
GO:0008289	lipid binding	0.005
GO:0004812	aminoacyl-tRNA ligase activity	0.01
GO:0005506	iron ion binding	0.03
GO:0005216	ion channel activity	0.003



# Conclusions

- Method for predicting function using Rosetta protein predictions

- Accurately match protein predictions to known structures
- Accurately prediction functions
- Integrate multiple pieces of evidence to increase coverage
- Predict specific and unique functions



# Acknowledgements

### Bonneau Lab

Glenn Butterfoss Thadeous Kacmarczyk Peter Waltman Aviv Madar Kevin Belasco Alex Pine Richard Bonneau

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Sasha Levy Peter McKenney Jane Carlton Dennis Shasha Kris Gunsalus Fabio Piano Patrick Eichenberger Biology Department

### <u>IBM</u>

Viktors Berstis Keith J Uplinger Bill Boverman

Funding

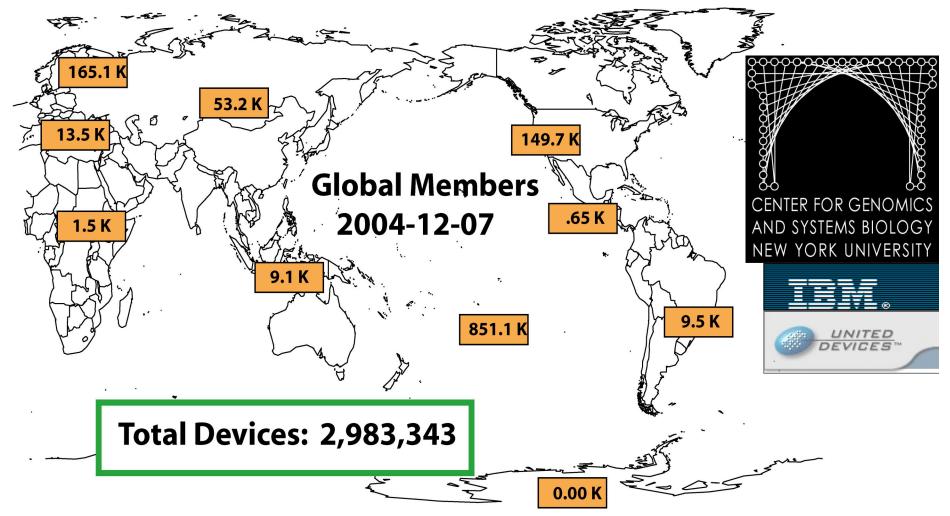
DOE NSF

<u>Rosetta-</u> <u>Commons</u>

Data & Results: http://www.yeastrc.org/pdr/

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### **GRID.ORG**



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