

# Statistical approaches to detect pathogenic variants of the *BRCA2* oncogene

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ABCS "Statistics for Lunch," 8 October 2024



## Biology + Statistics

**Focus:** statistics as an essential means of solving a biological problem

**“Disclaimer:”** we present a statistician’s perspective!



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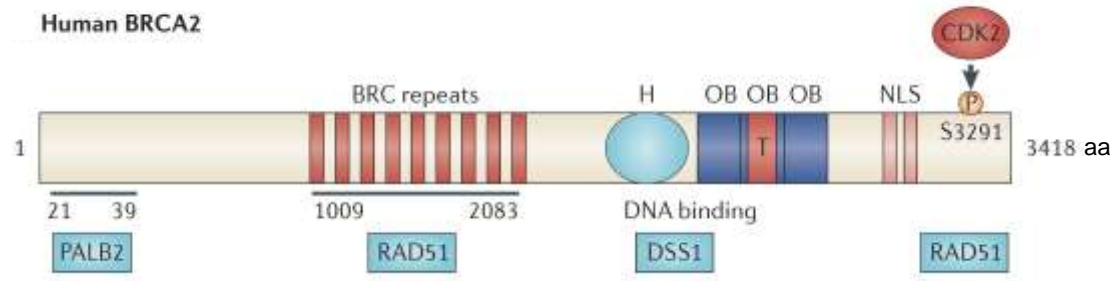
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Full details (including all the biology):

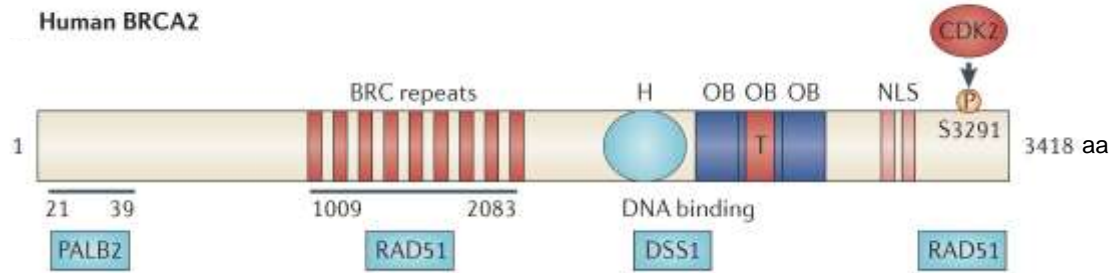
- Biswas, Mitrophanov, ..., Sharan (2023) *Cell Rep Methods* **3**: 100628
- Sahu, Sullivan, Mitrophanov, ..., Sharan (2023) *PLOS Genet* **19**: e1010940

# Pathogenicity of *BRCA2* oncogene variants needs assessment

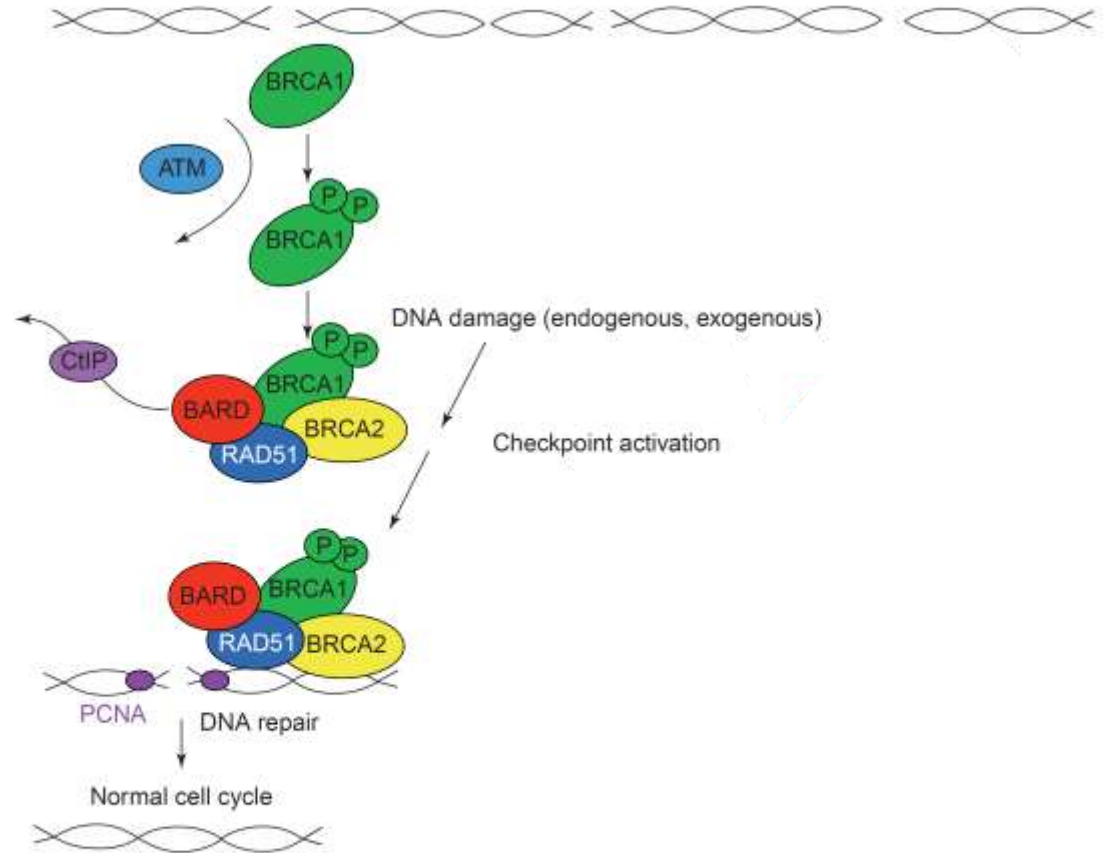


Roy *et al.*, *Nat Rev Cancer* 2012

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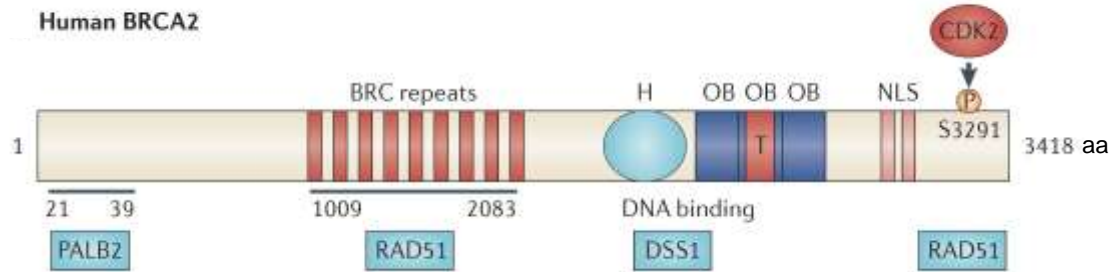


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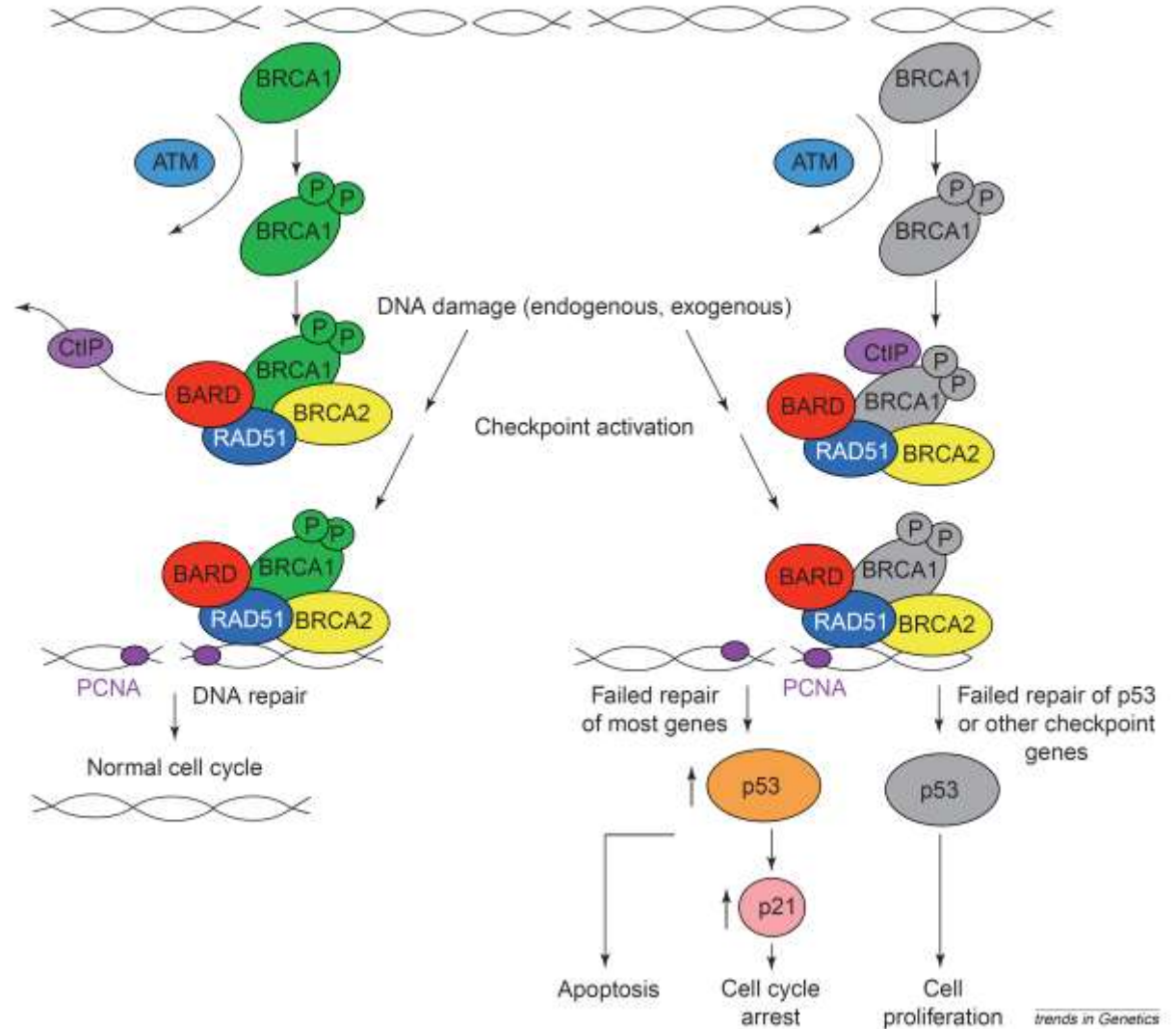


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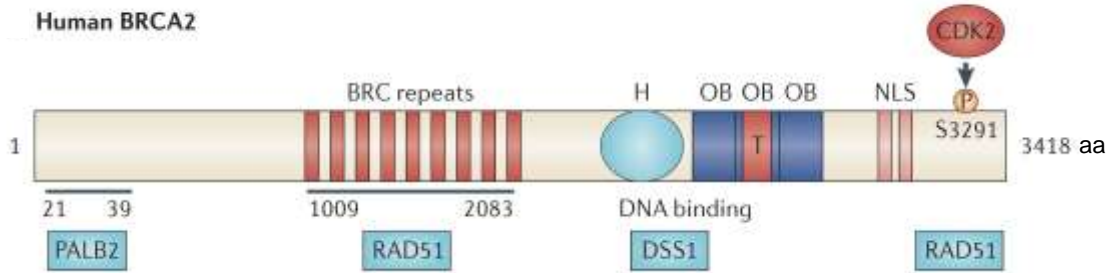


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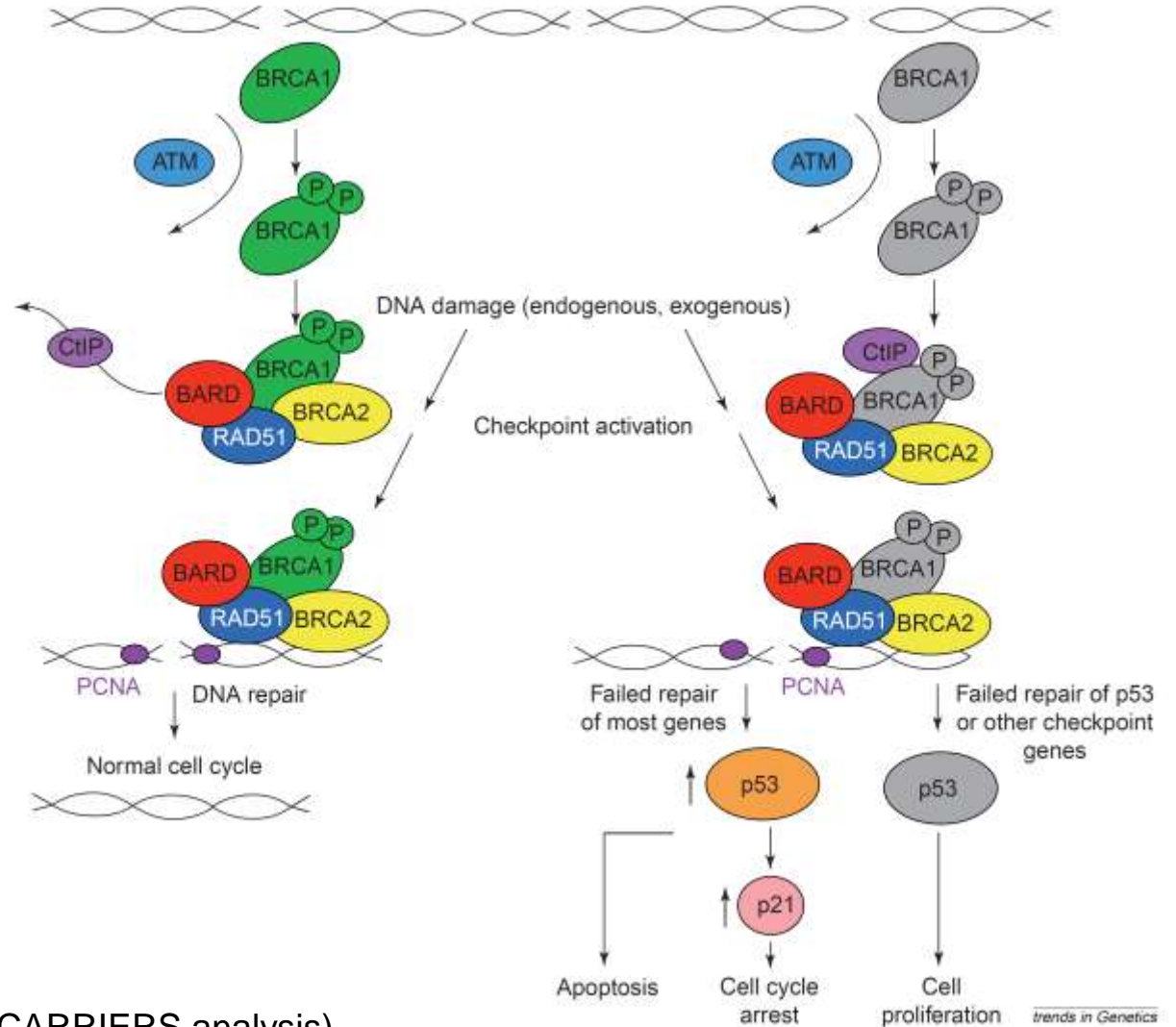
*BRCA2* sequence mutations



Different *BRCA2* variants



Predisposition to breast and ovarian cancer

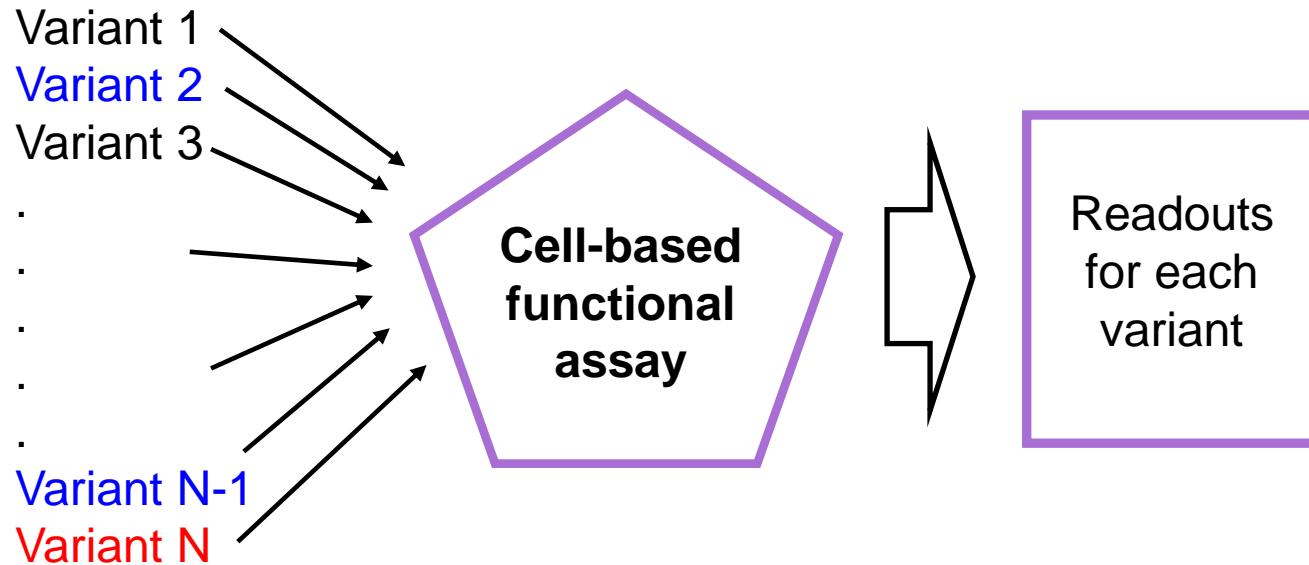


~1.3% breast-cancer patients have pathogenic *BRCA2* variants (CARRIERS analysis)  
17,000+ *BRCA2* variants in ClinVar database; **3,000+ are of uncertain significance**

Welsh et al., Trends Genet 2000

# How do we know which *BRCA2* variants are likely to be pathogenic?

## By using a functional assay!



Red: pathogenic variant

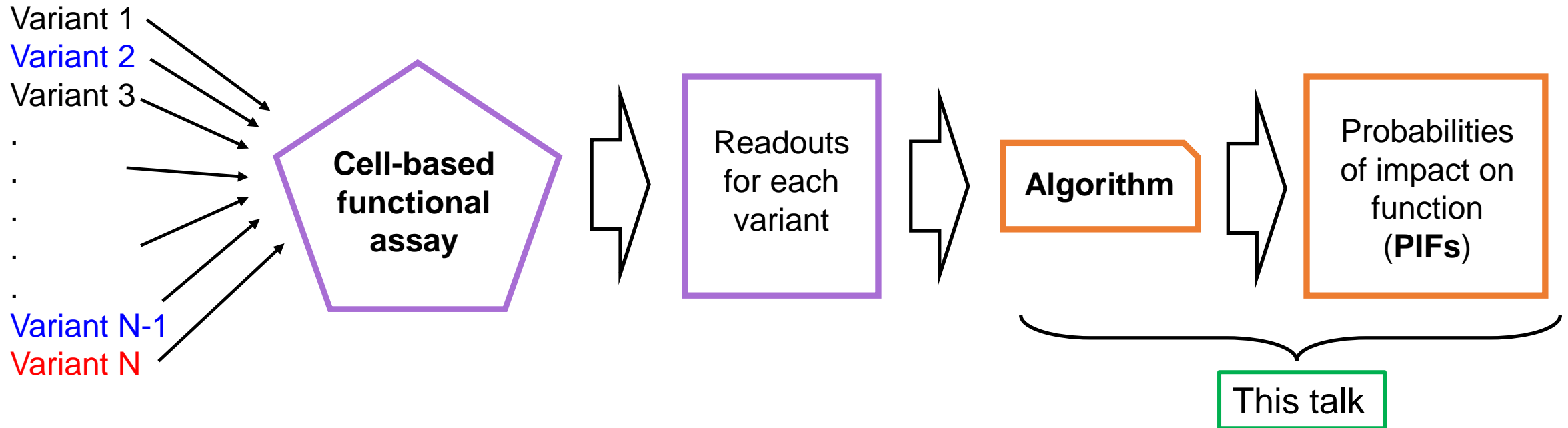
Blue: benign variant

Black: VUS (variant of uncertain significance)

**American College of Medical Genetics and Genomics:**

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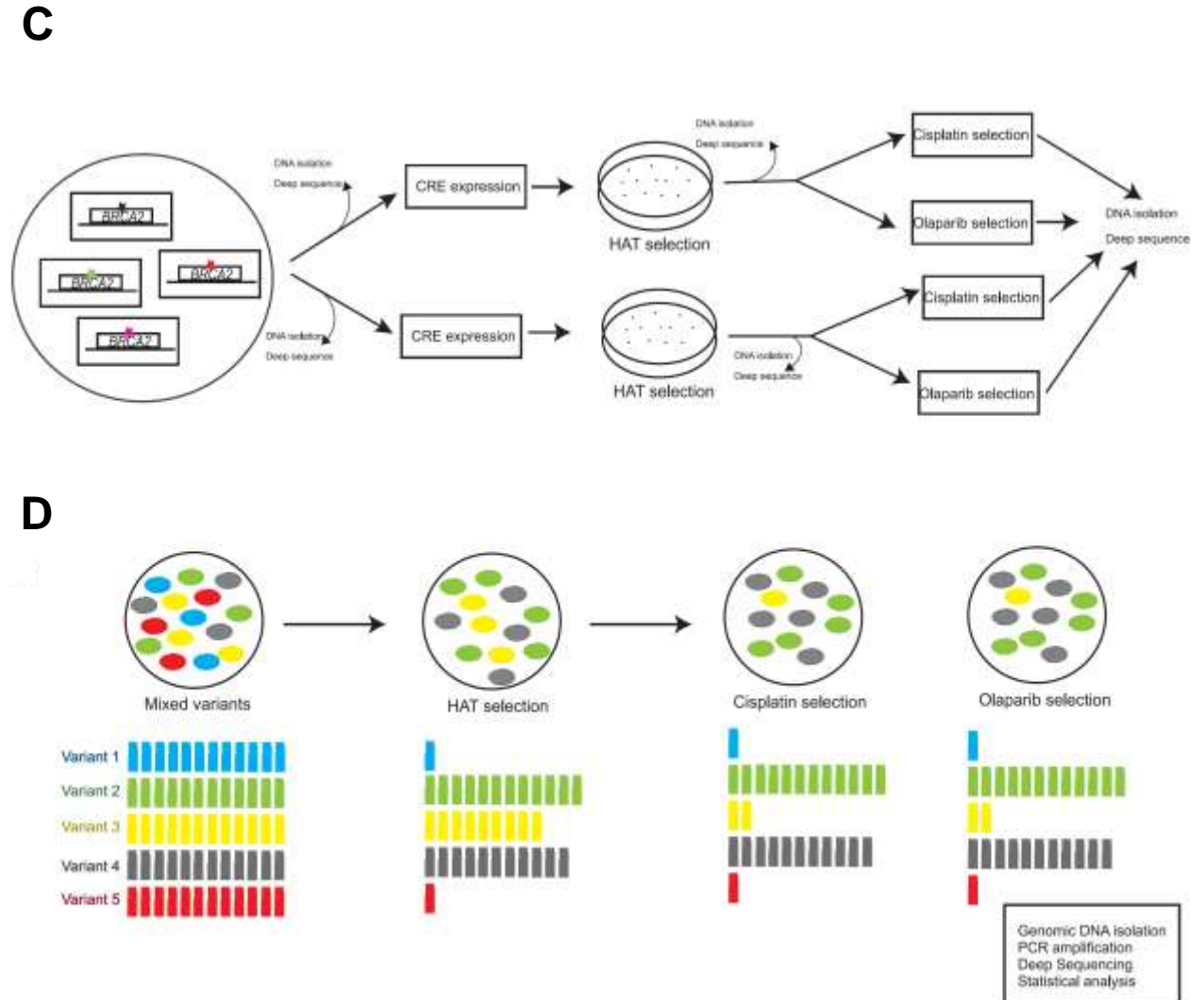
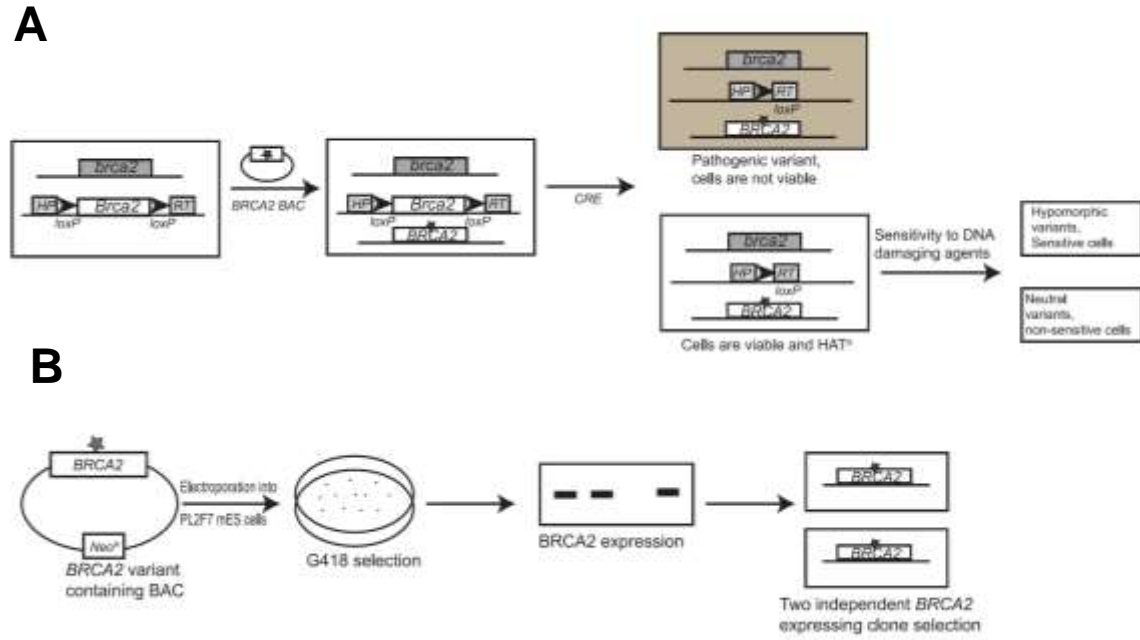
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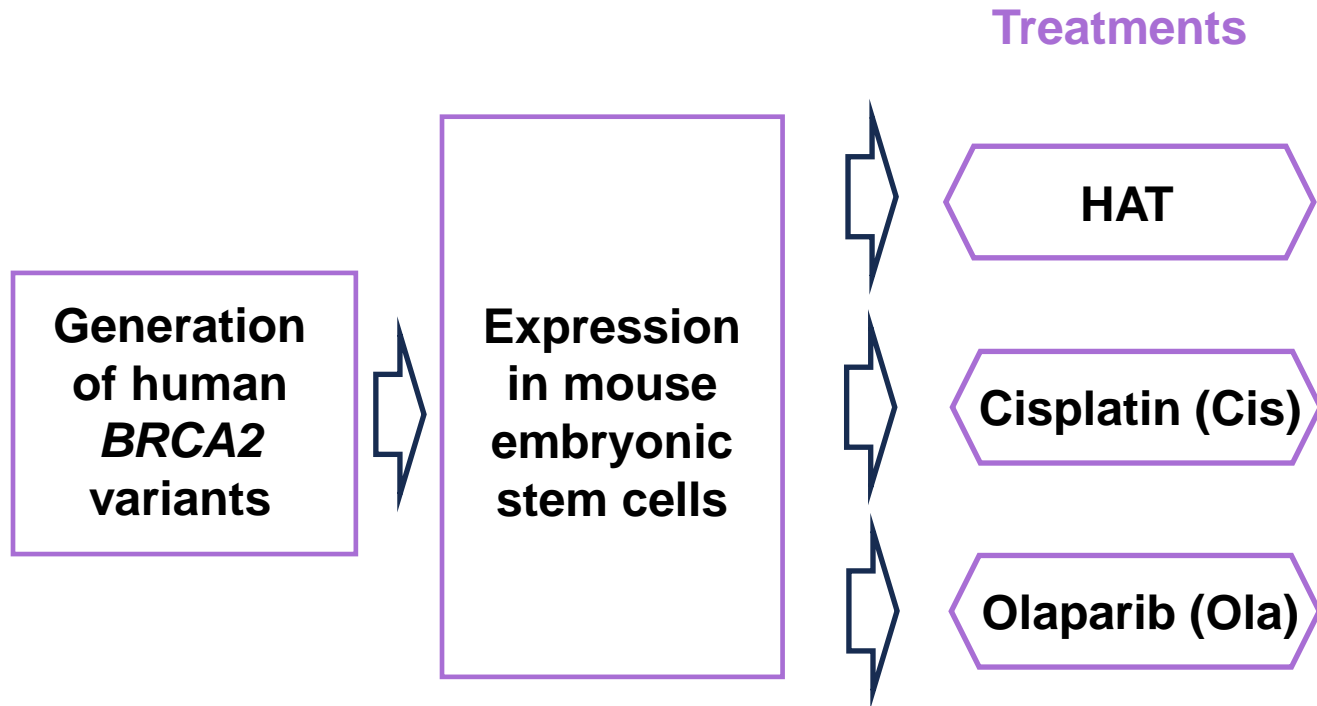
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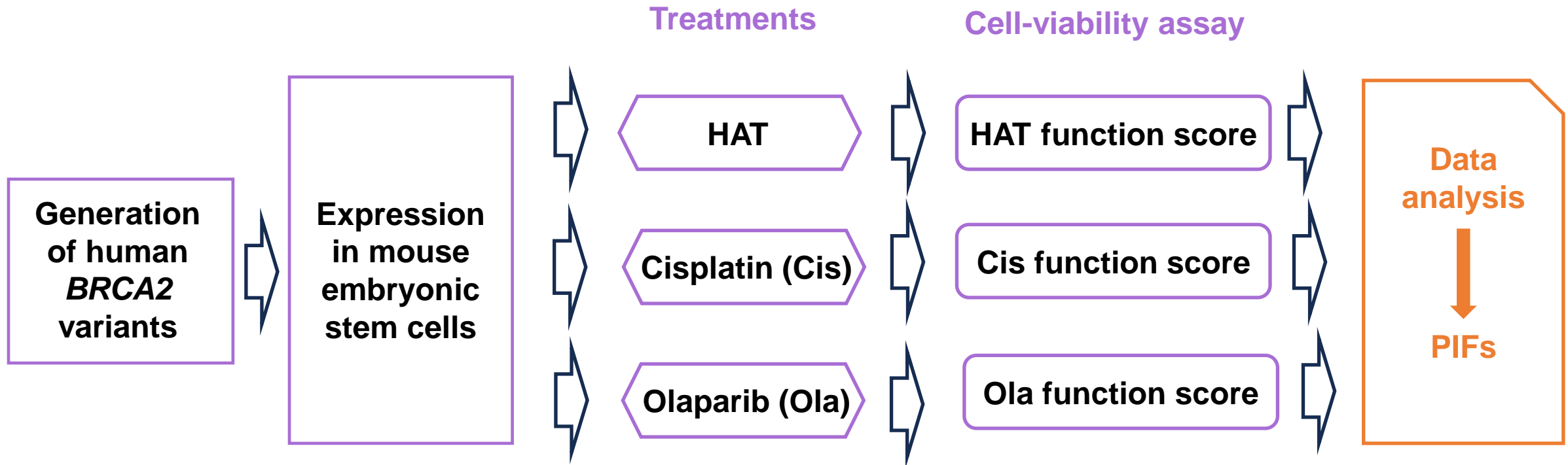
# Experimental setup for data generation for 223 *BRCA2* variants



# Experimental setup for data generation for 223 *BRCA2* variants (*streamlined*)



# Experimental setup for data generation for 223 *BRCA2* variants (streamlined)



**Function score:** frequency of variants in the final pool relative to the initial pool (determined via *next-generation sequencing*)

**One data point:** the function score for one **variable** (HAT or Cis or Ola) for one *BRCA2* variant

# Requirements for the statistical methodology

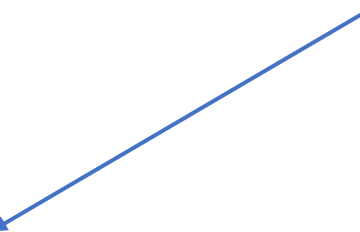
## Requirements

- Should calculate probabilities of impact on function (PIFs)
- The probabilities should not be “too binary”
- Should use the accepted PIF thresholds for **benign** and **pathogenic** ( $\leq 0.05$  and  $> 0.99$ , respectively)
- Should use **semi-supervised learning** (expected to outperform supervised-learning approaches; e.g., VarCall software)

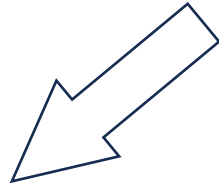
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- 
- **Supervised:** use only labeled data in model training (fitting)
  - **Semi-supervised:** use all available data in model training (fitting)

# Model assessment in statistics

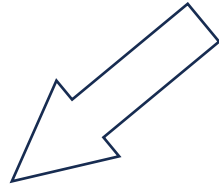


## Descriptive and inferential statistics

How well the model captures the statistical *distributions* in the data set; how well it allows us to characterize the *distributions* in the general population based on the statistical sample

We use this during model construction

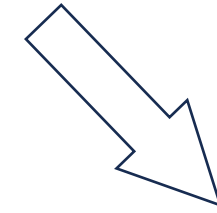
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## Our main approach

## Statistical learning and machine learning (AI, etc.)

Predictive performance !!!

Standard measures: **accuracy** (fraction of correctly predicted **benign** and **pathogenic** variants), **sensitivity** (fraction of correctly predicted **pathogenic** variants), **specificity** (fraction of correctly predicted **benign** variants)

Standard approach: cross-validation (train the model on a subset of the data, test on the other subset; repeat for different data partitions)

# Initial analysis and approaches

## Technical decisions made (data preprocessing)

- Should we filter out outliers?
- What do we do with the two “data pools” (biological replicates)?
- Should we log-transform the data?
- ...(many more)

# Initial analysis and approaches

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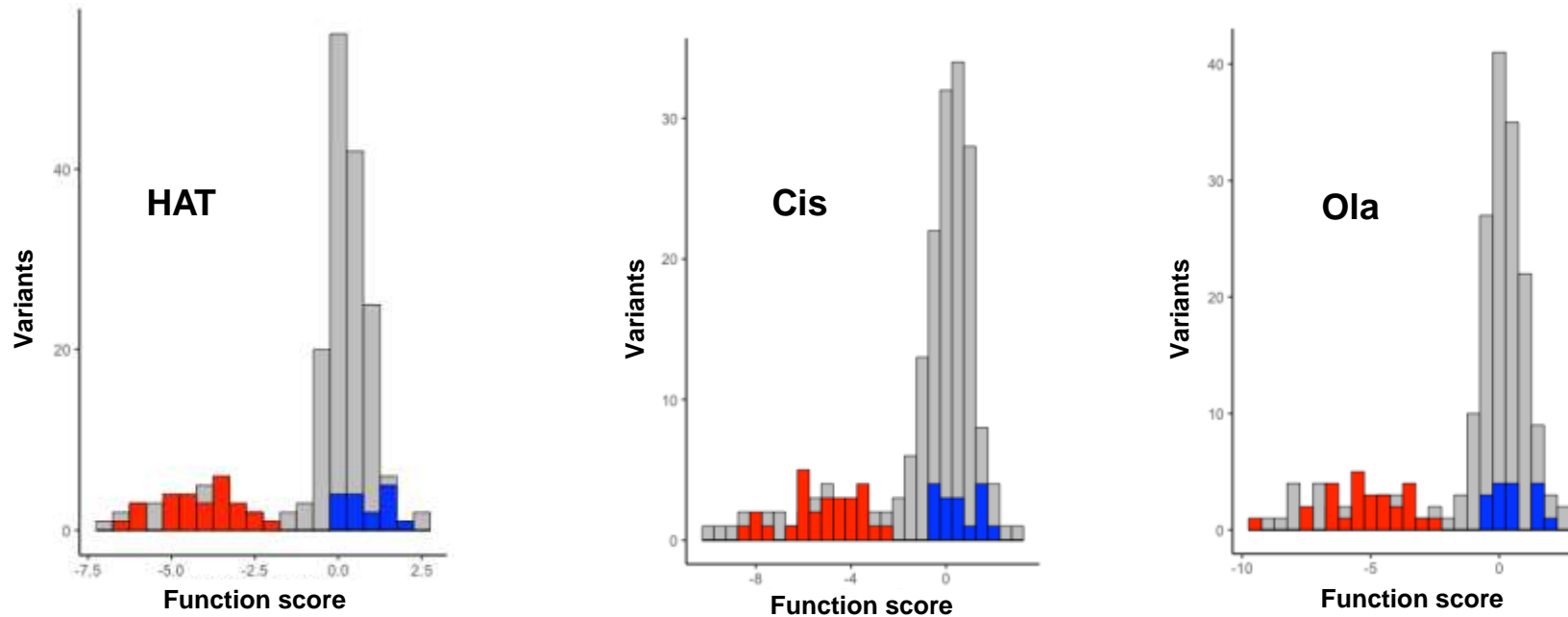
## Statistical approaches considered

- Logistic regression
- Linear and quadratic discriminant analysis
- Mixture modeling with non-normal components
- Supervised-learning approach to mixture modeling

# The approach that worked

$N = 223$  *BRCA2* variants;  $N_b = 16$  labeled benign and  $N_p = 27$  labeled pathogenic  
(the rest,  $N_u$ , are VUS = variants of uncertain significance)

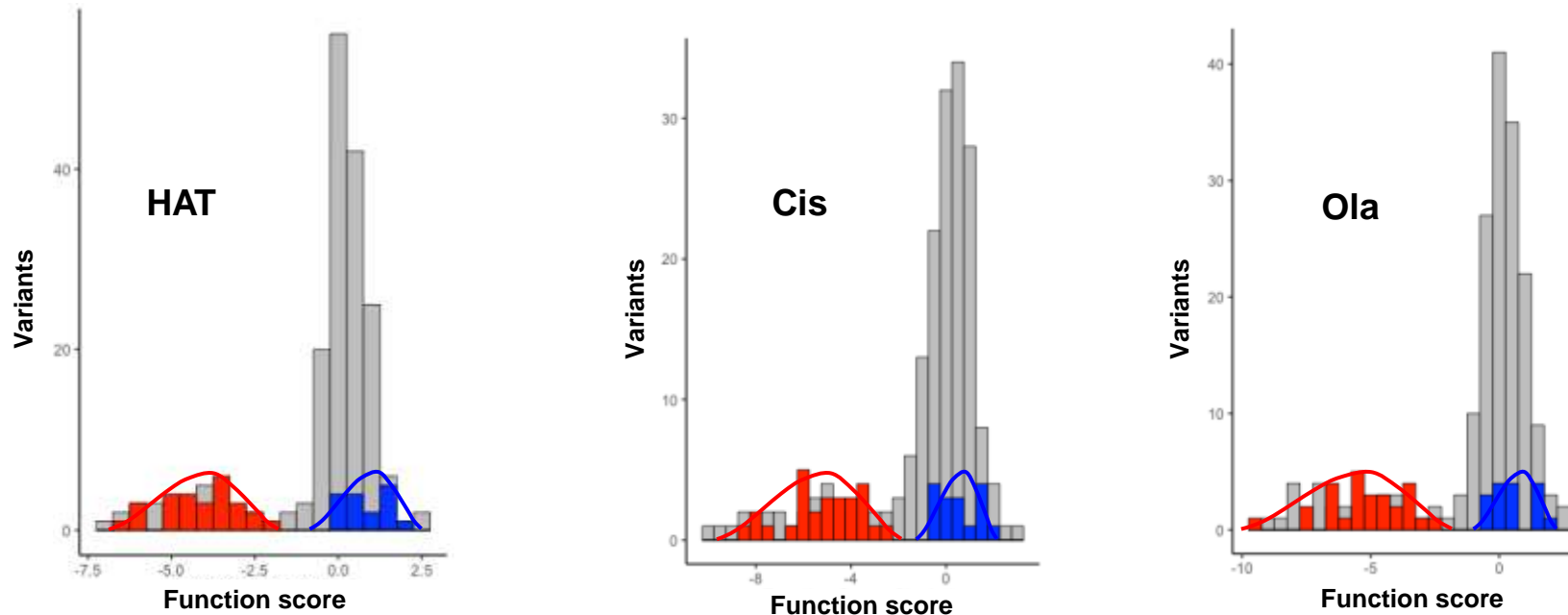
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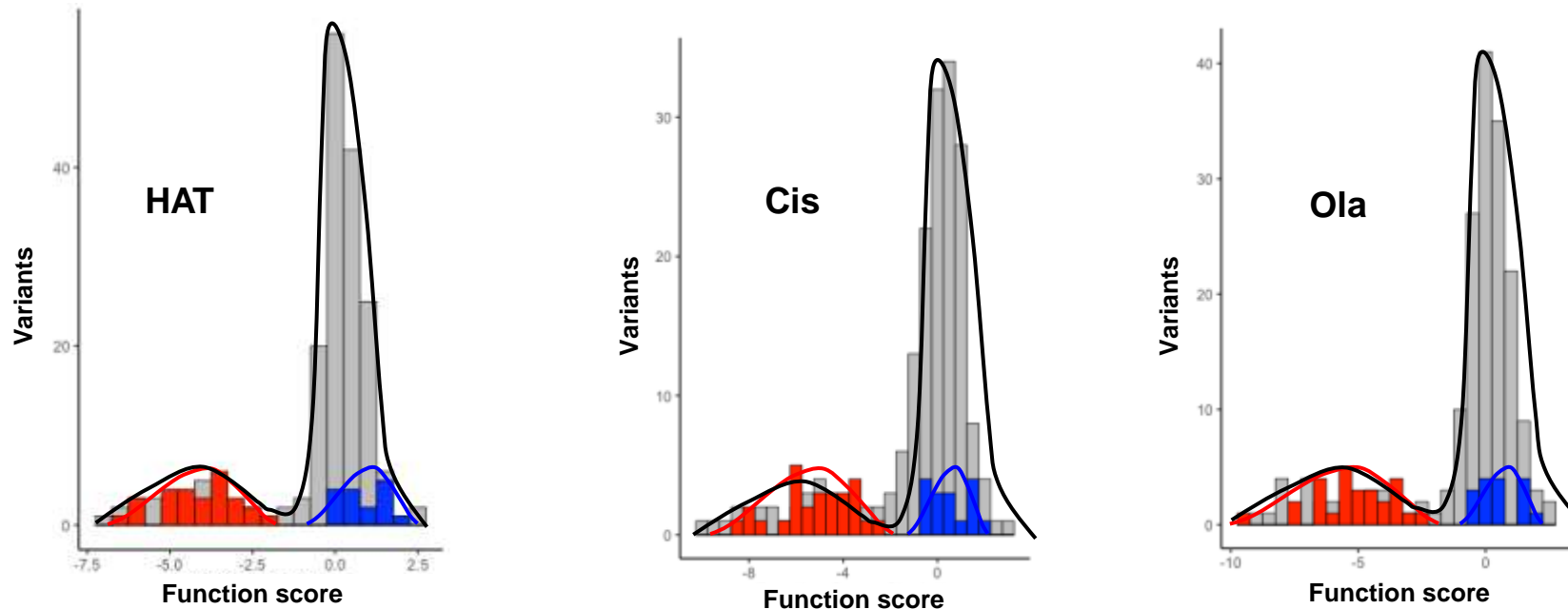


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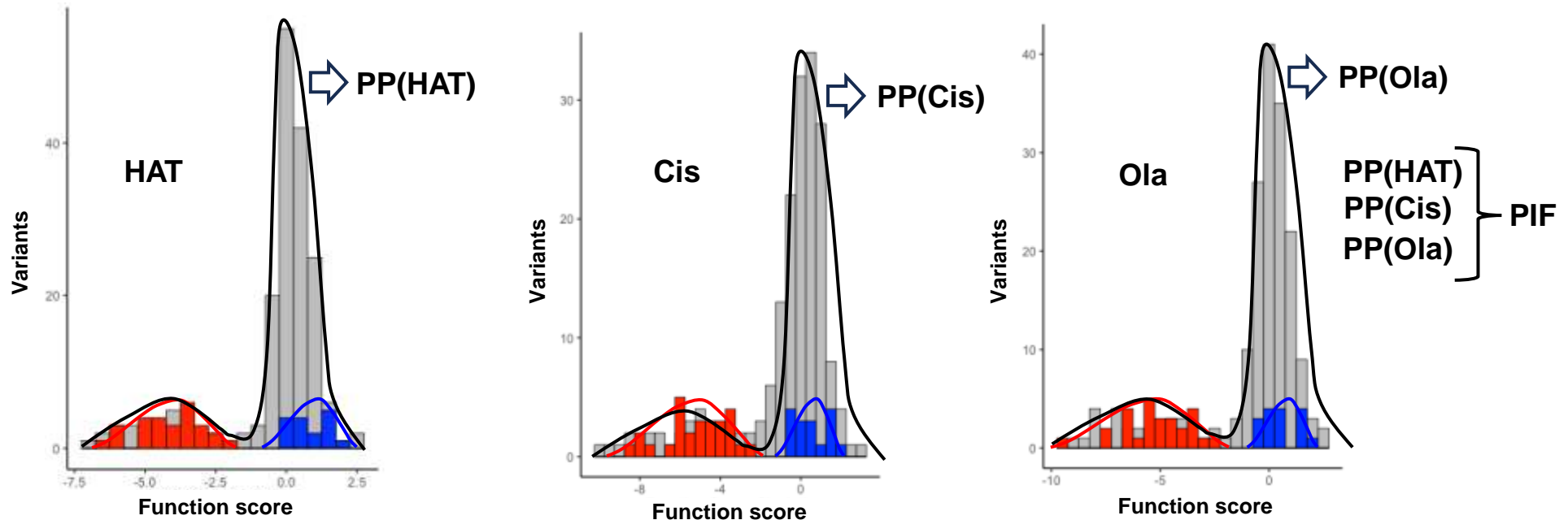


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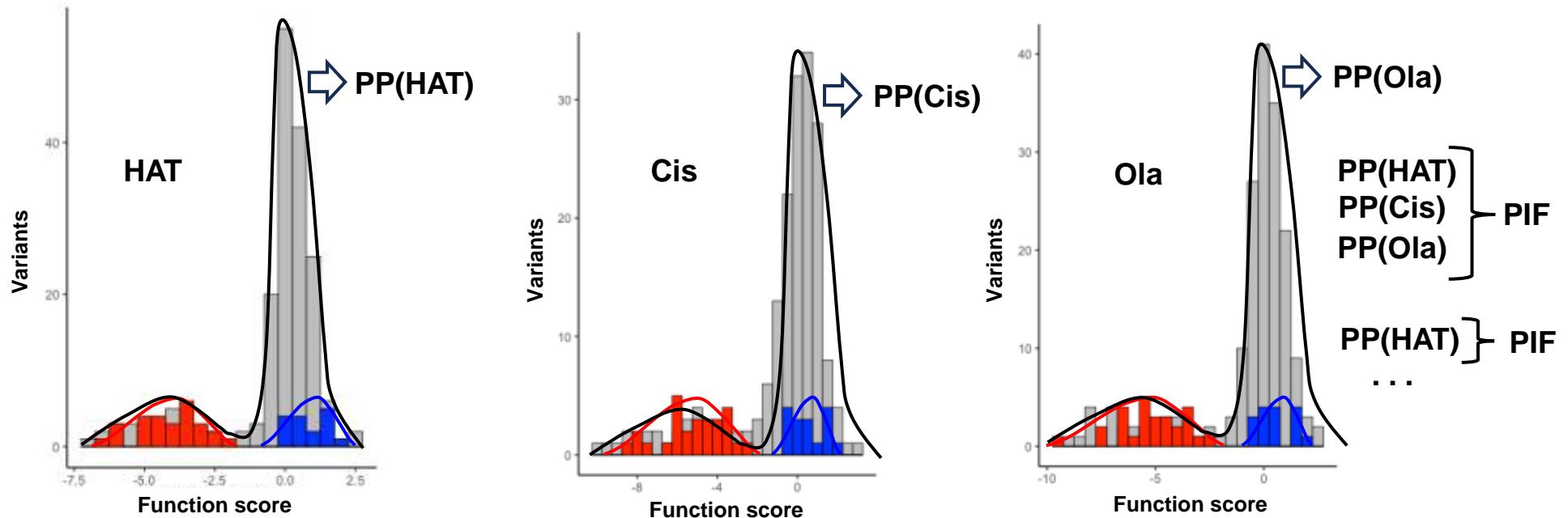


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- Use the parameters from the fits with some math to calculate PIFs (probabilities of impact on function)
- Consider alternative models (supervised-learning and/or one input variable only, **HAT** or **Cis** or **Ola**)

# Our main methodology: mixture modeling + semi-supervised learning + empirical Bayes + heuristics

- $N = 223$  *BRCA2* variants;  $N_b = 16$  labeled benign and  $N_p = 27$  labeled pathogenic (the rest,  $N_u$ , are VUS = variants of uncertain significance)
- 3 numerical variables: **HAT**, **Cis**, and **Ola** (function scores), with values for every *BRCA2* variant
- For each variable, distribution density is modeled independently as a normal mixture:

$$g(x, p, m_p, v_p, m_b, v_b) = pf(x, m_p, v_p) + (1 - p)f(x, m_b, v_b)$$

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- Parameters are estimated via maximum-likelihood fits (semi-supervised learning):

$$l(p, m_p, v_p, m_b, v_b | \mathbf{x}) = \prod_{i=1}^{N_p} pf(x_i^{(p)}, m_p, v_p) \times \prod_{i=1}^{N_b} (1 - p)f(x_i^{(b)}, m_b, v_b) \times \prod_{i=1}^{N_u} g(x_i^{(u)}, p, m_p, v_p, m_b, v_b)$$

- Bayes formula (empirical Bayes) for probabilities of pathogenicity:

$$PP_i = \frac{pf(x_i, m_p, v_p)}{g(x_i, p, m_p, v_p, m_b, v_b)}$$

- Heuristic PIF formulas for each *BRCA2* variant:

**Full:**  $PIF_i = PP_i(HAT) + (1 - PP_i(HAT))PP_i(Cis)PP_i(Ola)$

**Alt.:**  $PIF_i = PP_i(HAT)$  OR  $PIF_i = PP_i(Cis)$  OR  $PIF_i = PP_i(Ola)$

# Validation of the computational predictions

**Internal validation:** K-fold cross-validation (CV) with  $K = 3, 6, 9, 43$  ( $K = 43$  is leave-one-out CV)

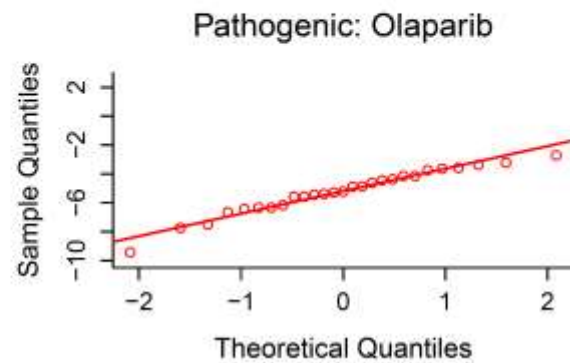
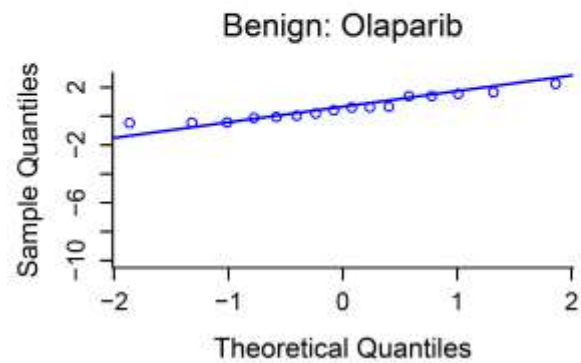
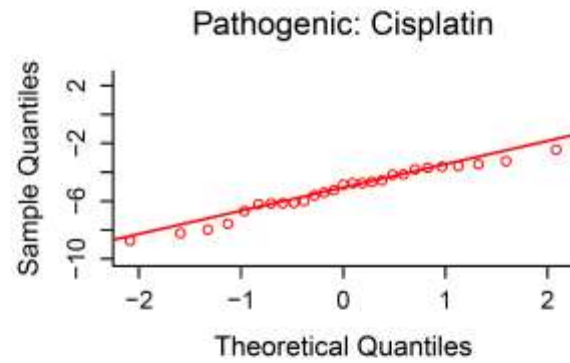
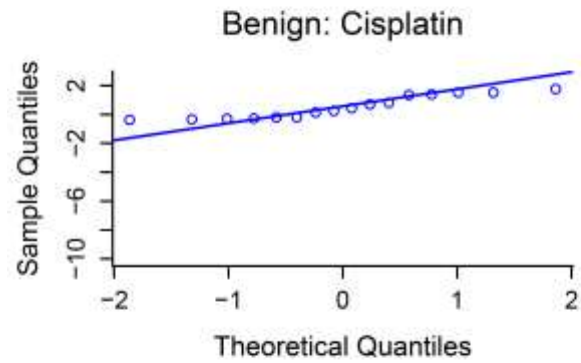
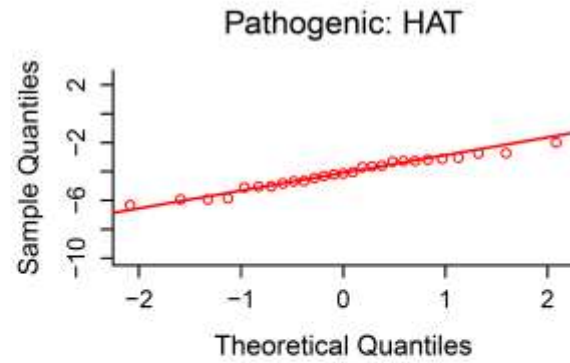
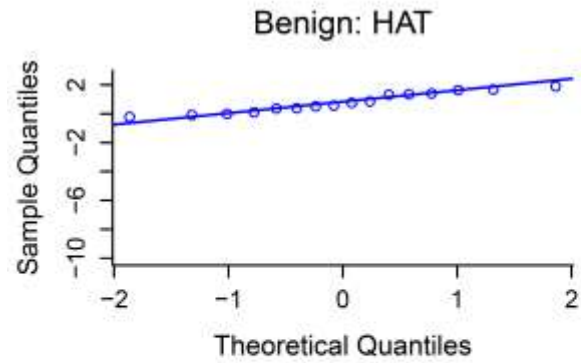
Basis: fixed **benign** and **pathogenic** PIF thresholds ( $\leq 0.05$  and  $> 0.99$ , respectively)

Main performance metric: **accuracy** (% correctly classified *BRCA2* variants, averaged across folds)

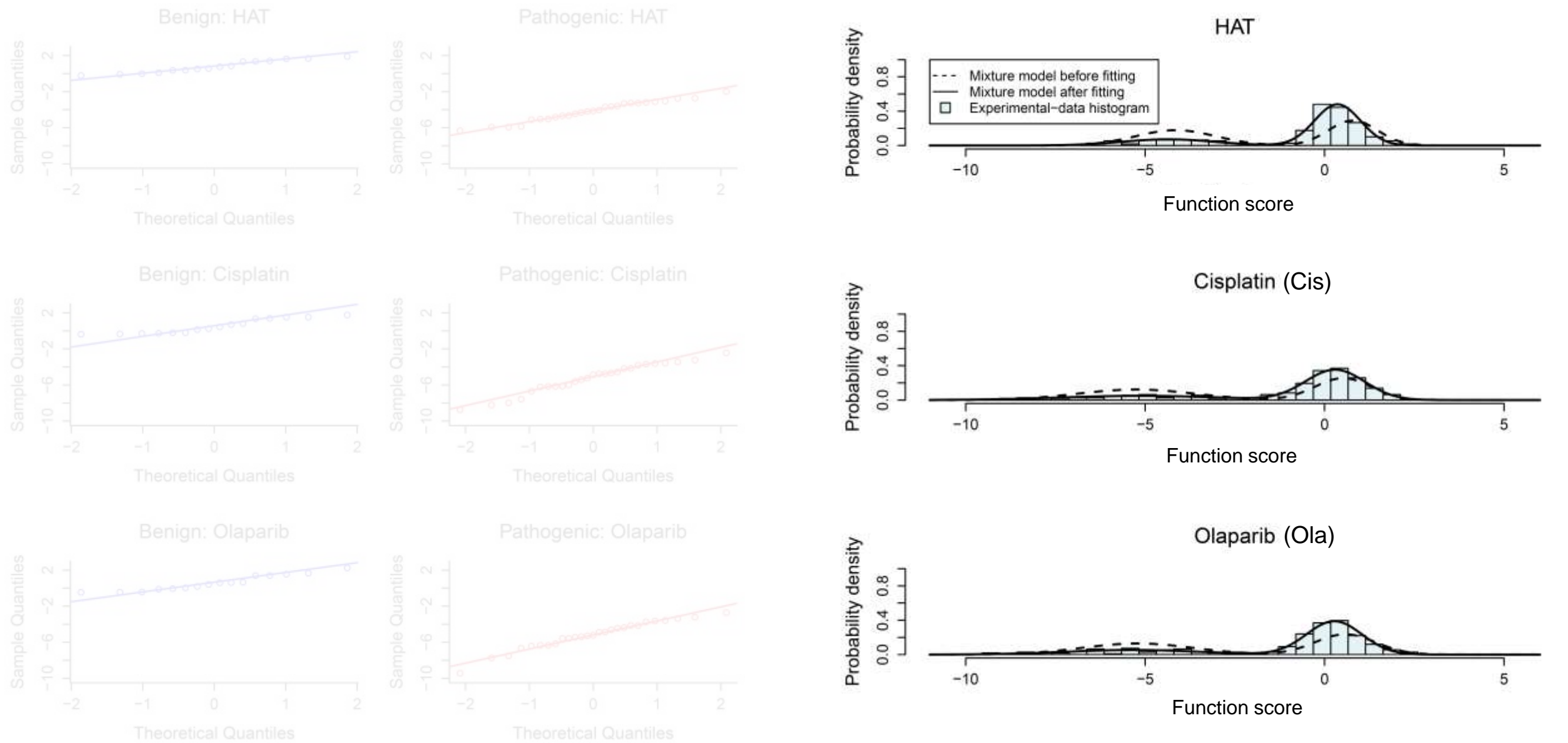
Full algorithm version (semi-supervised, HAT + Cis + Ola):  
CV accuracy = 100% for all  $K$  values

**External validation:** information from diverse sources

# Results for data distributions: normality and fitting (mixture model)

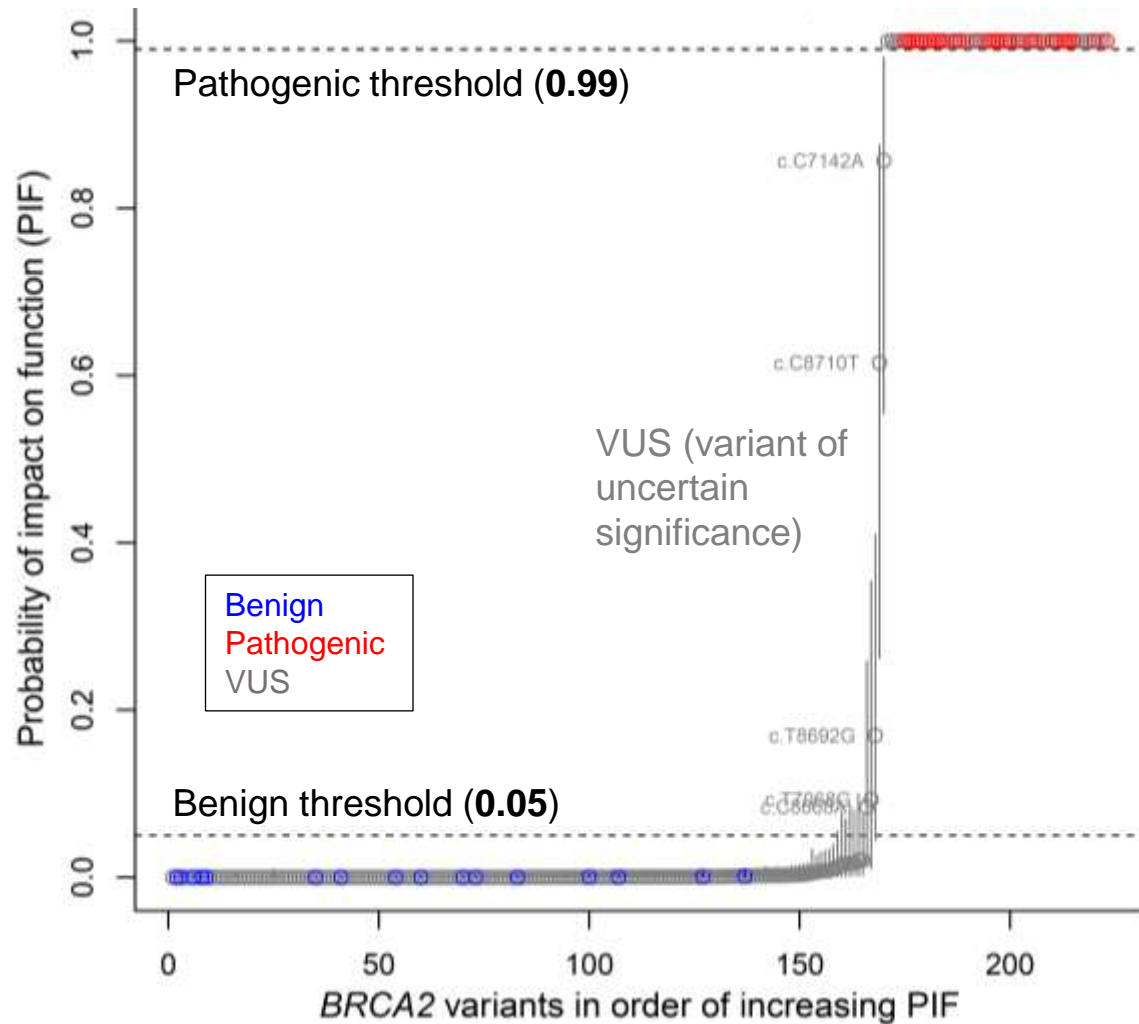


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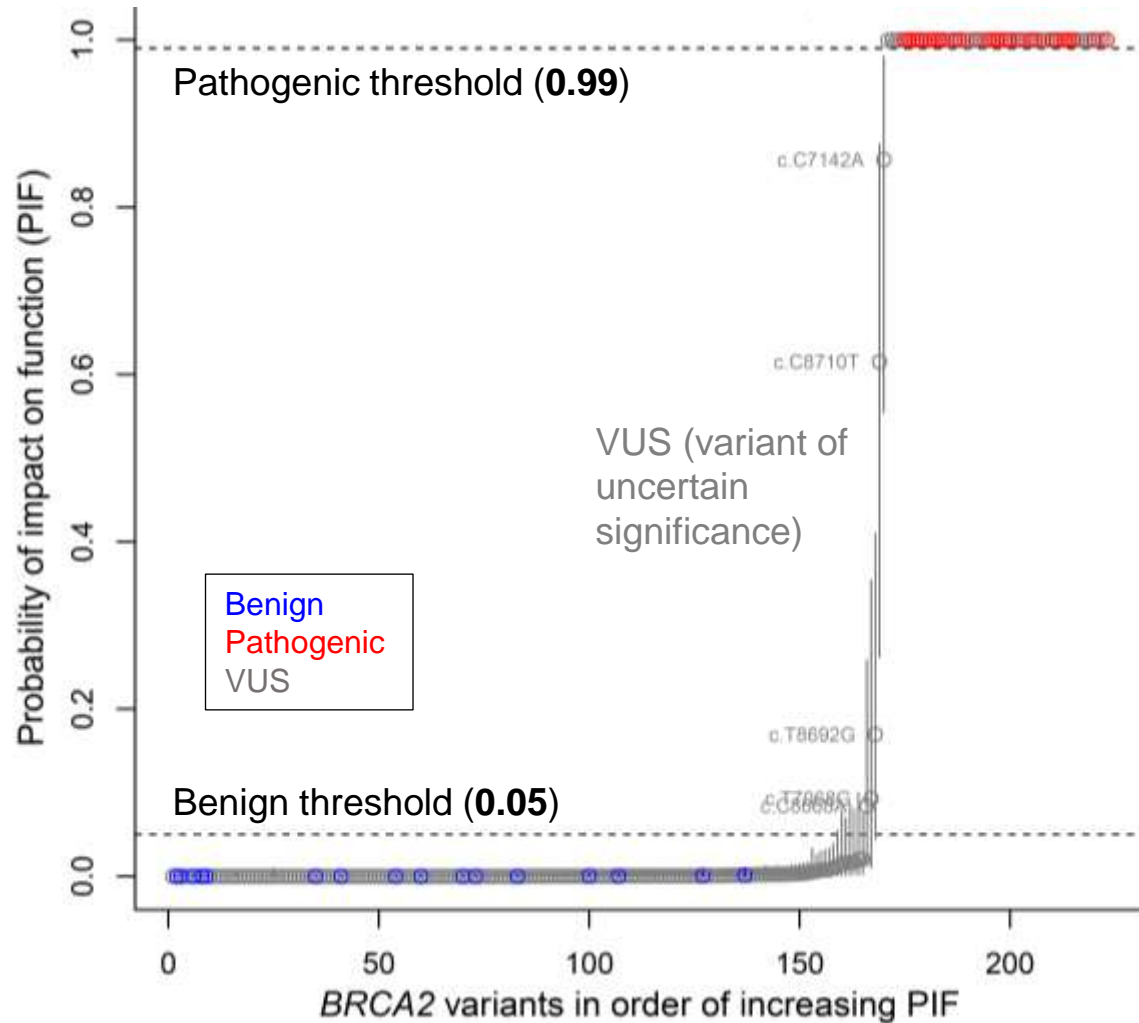
# Computed probabilities of impact on function (PIFs)

Full model: HAT + Cisplatin + Olaparib

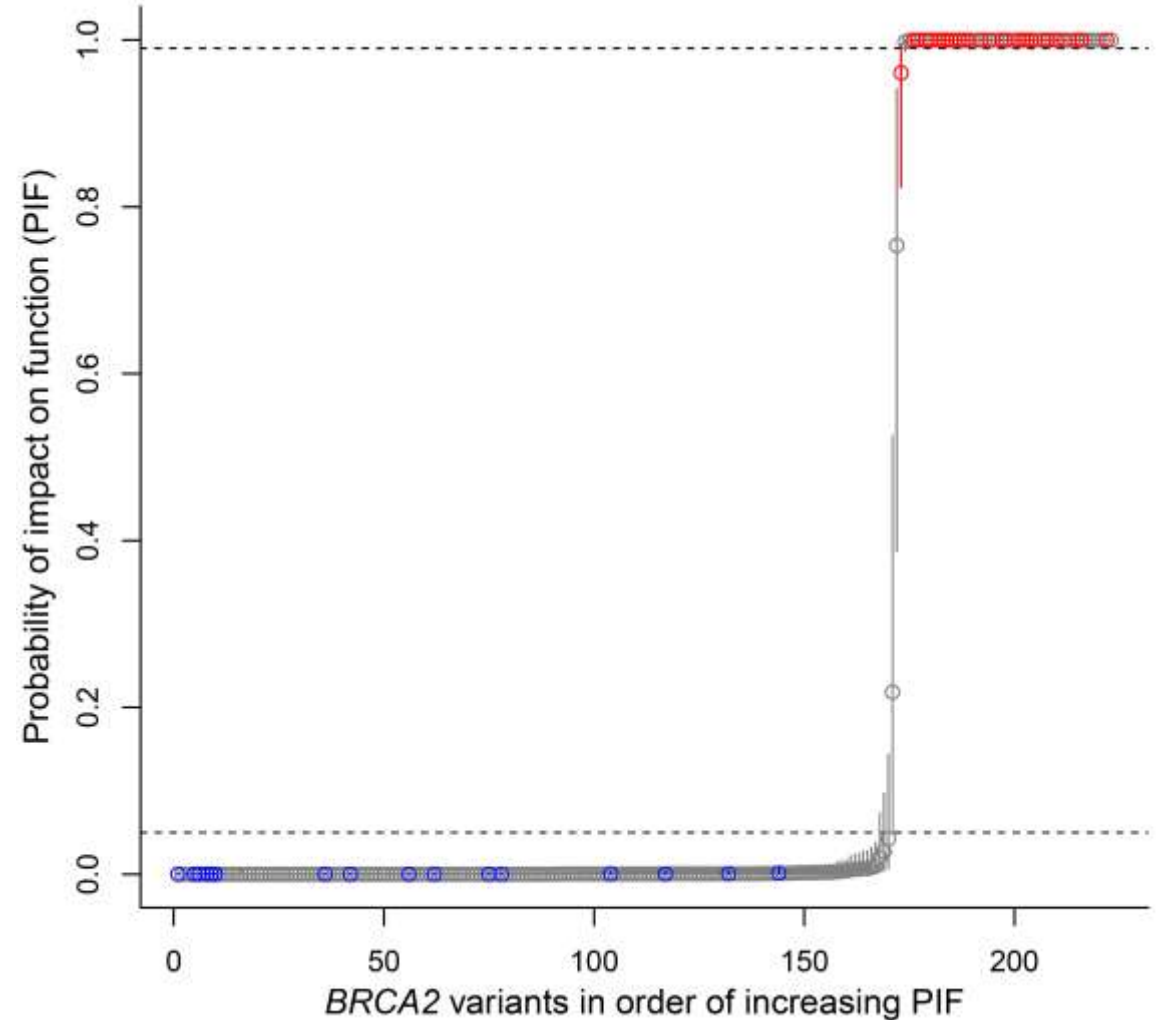


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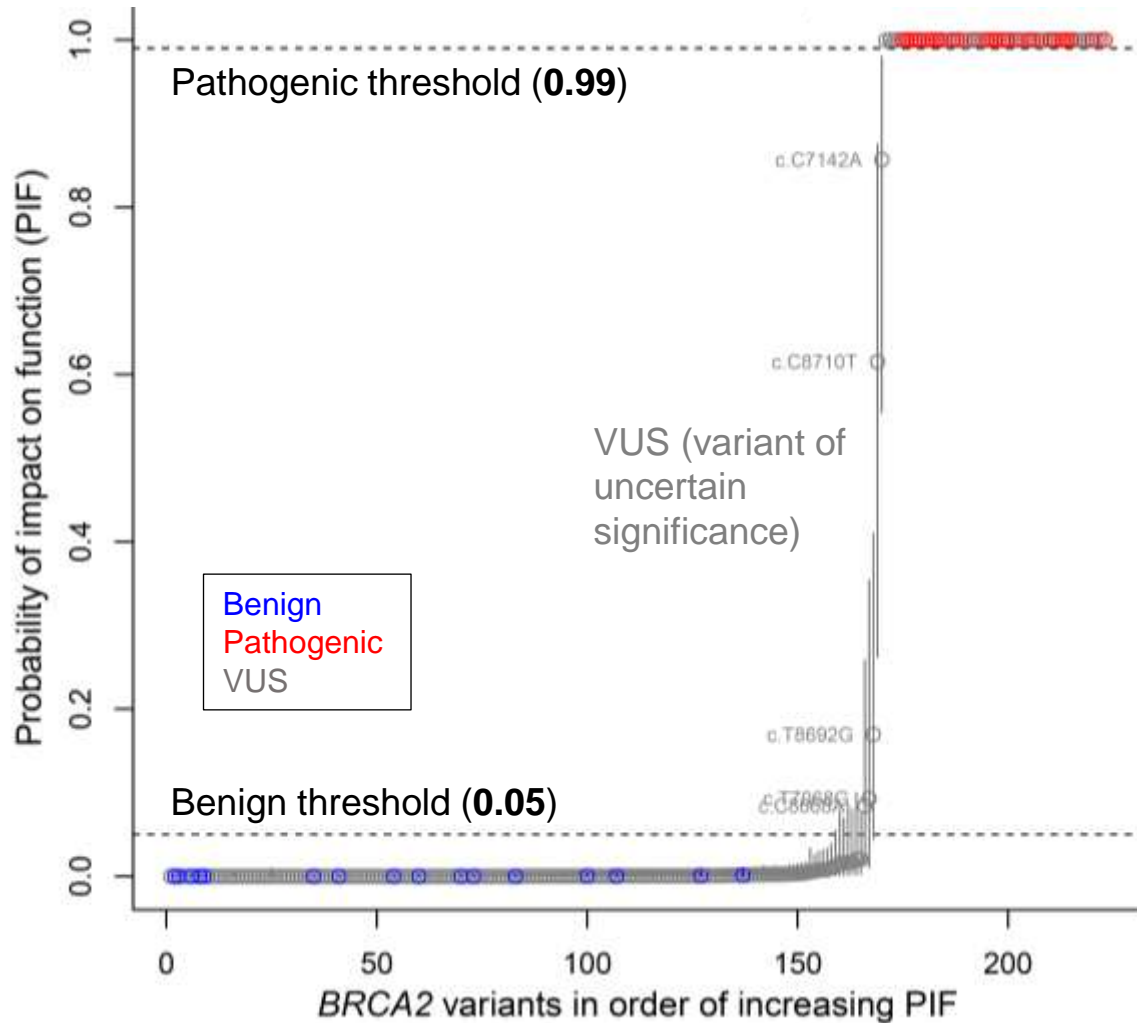


HAT

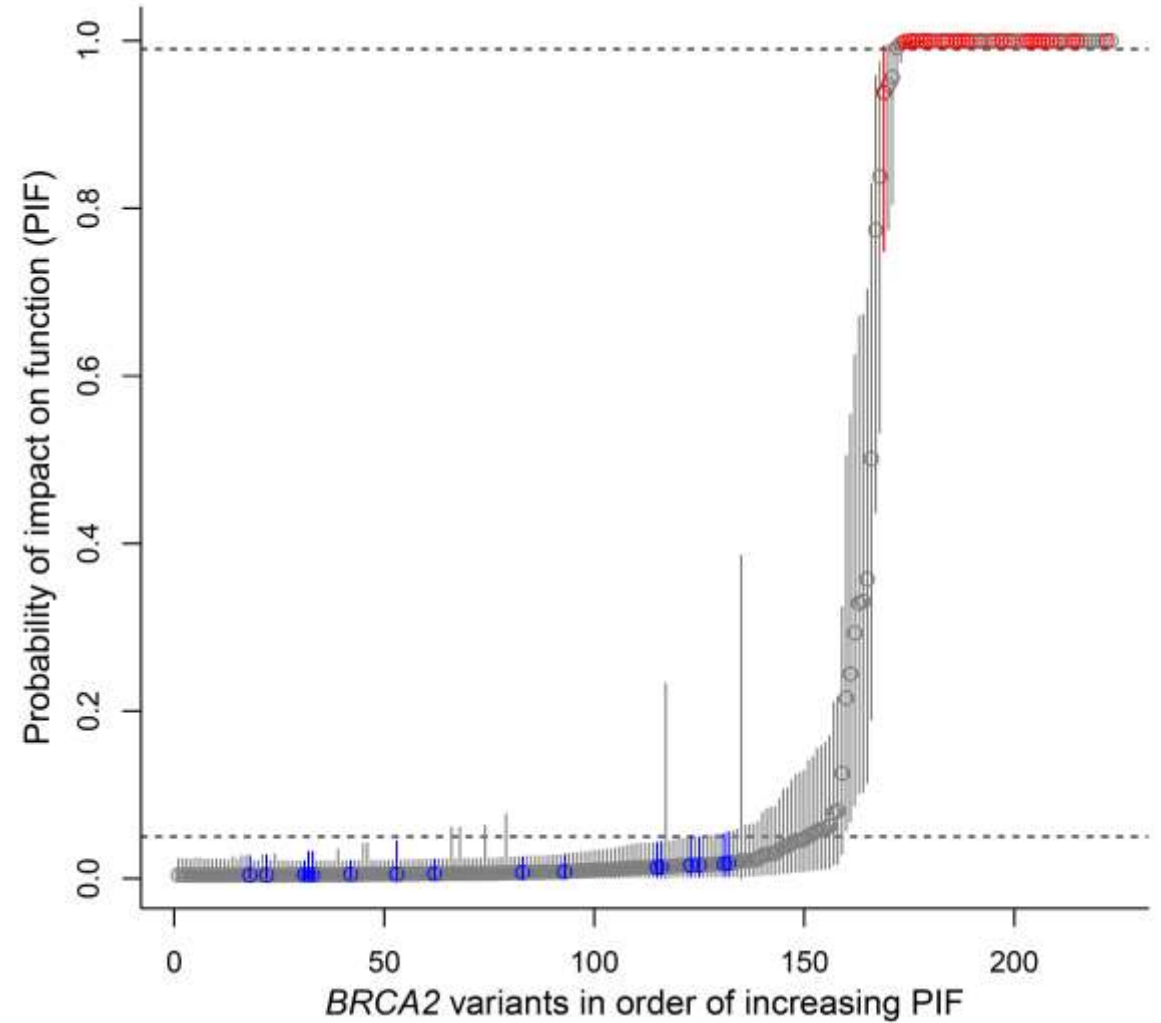


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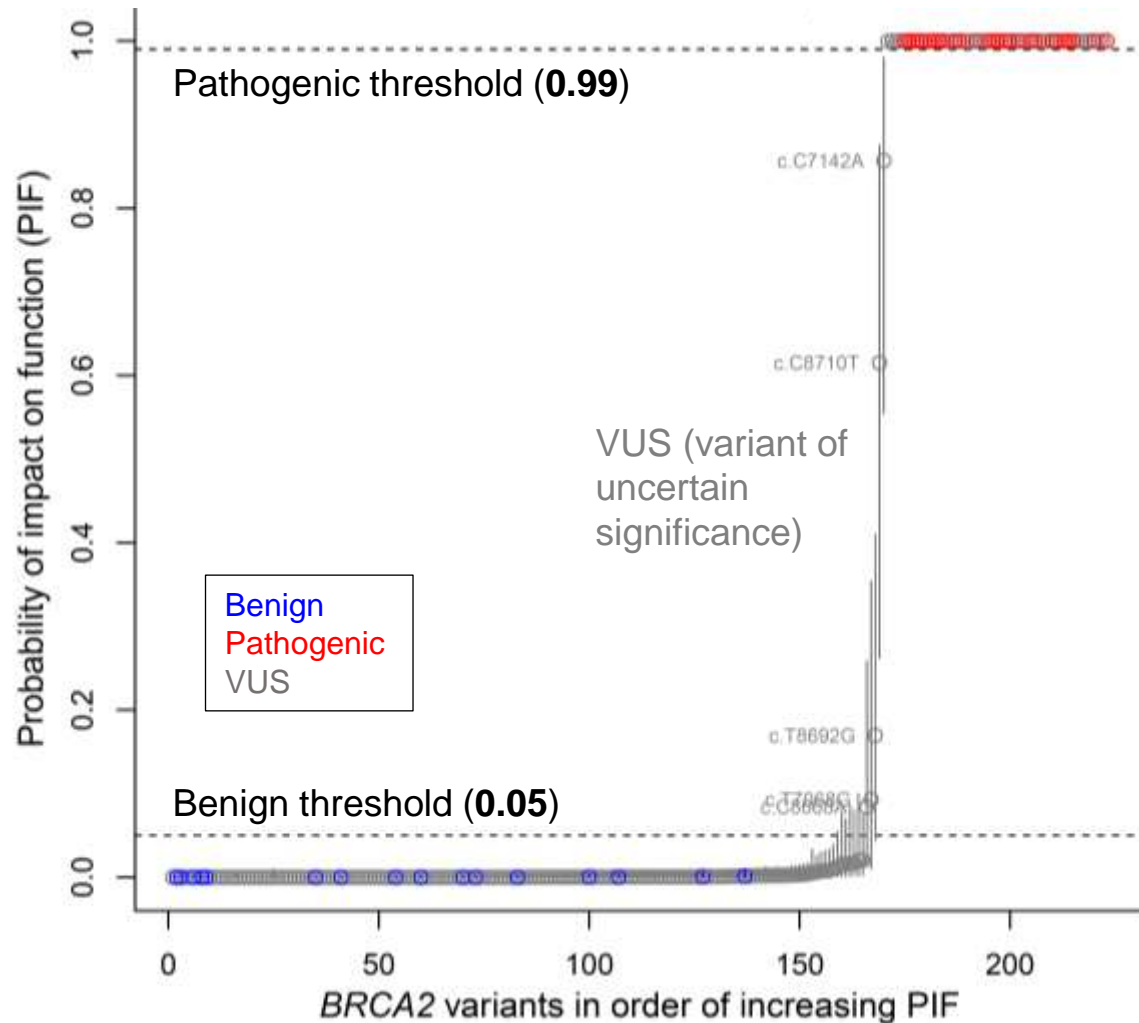


Cisplatin

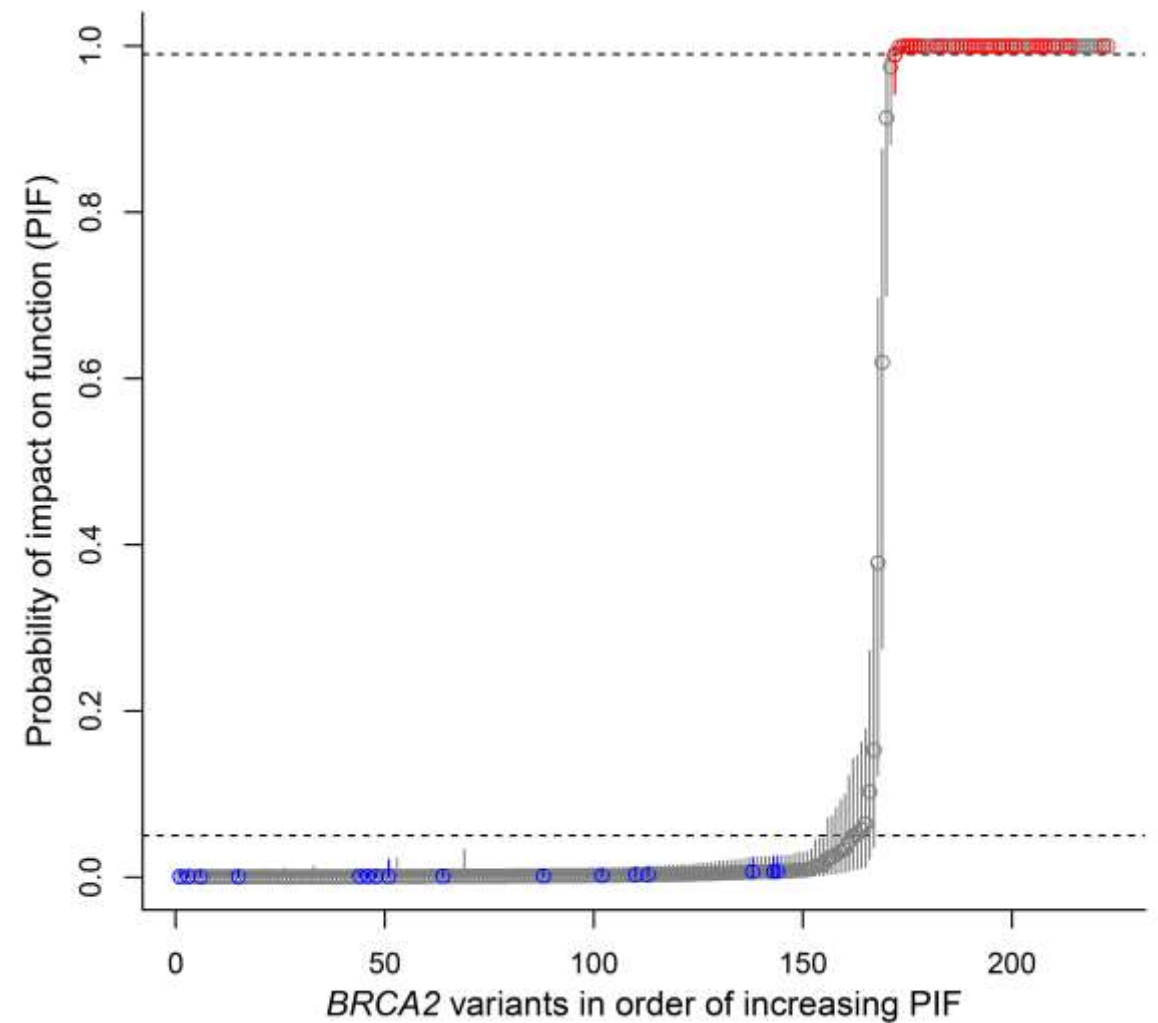


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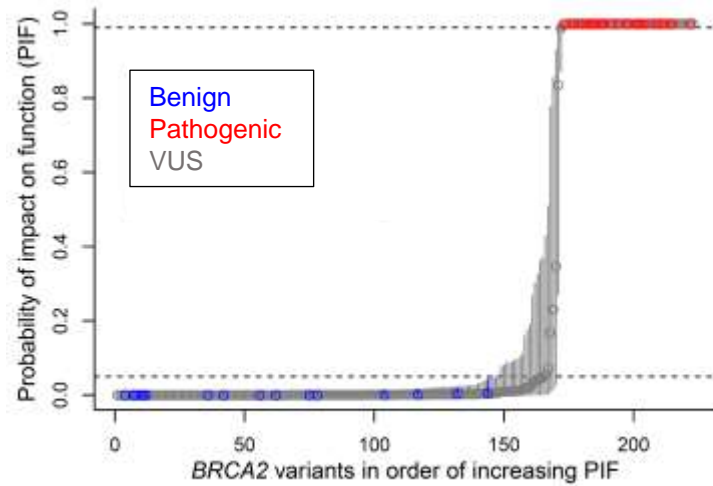
Olaparib



# **Computed probabilities of impact on function (PIFs): supervised learning**

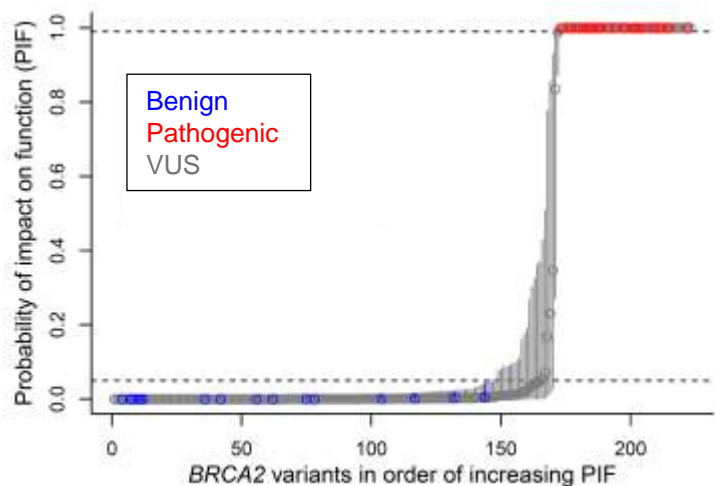
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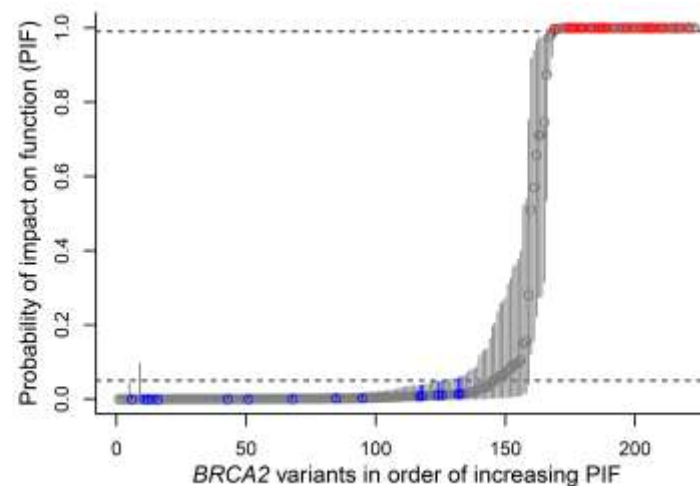


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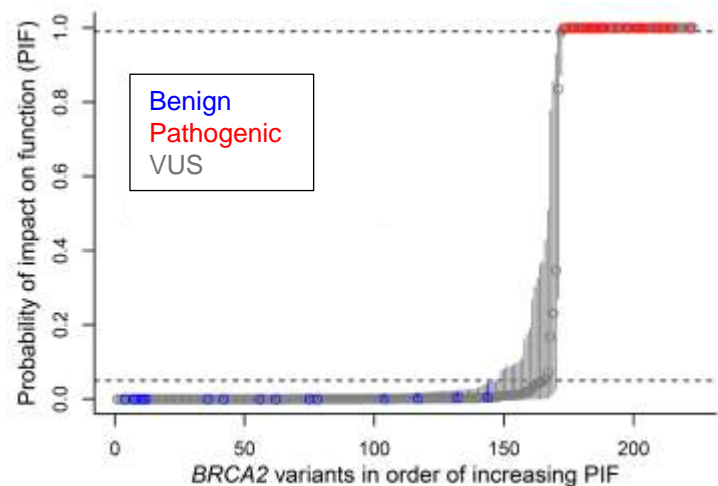


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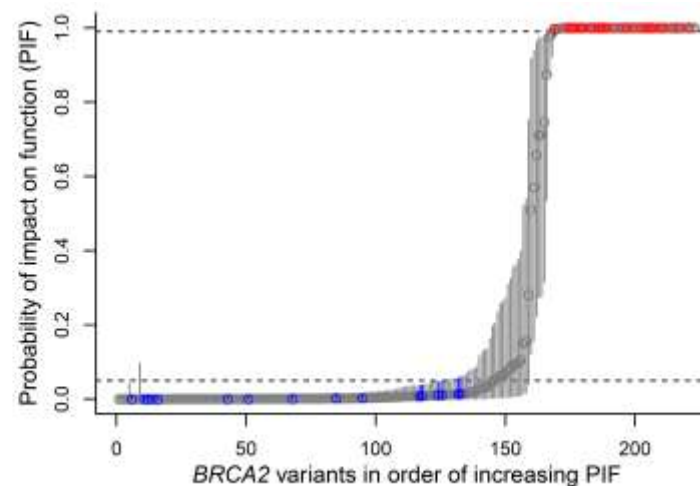


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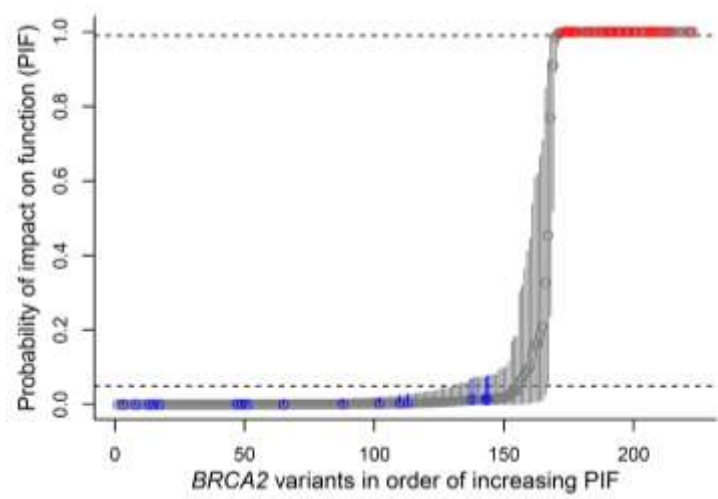
HAT



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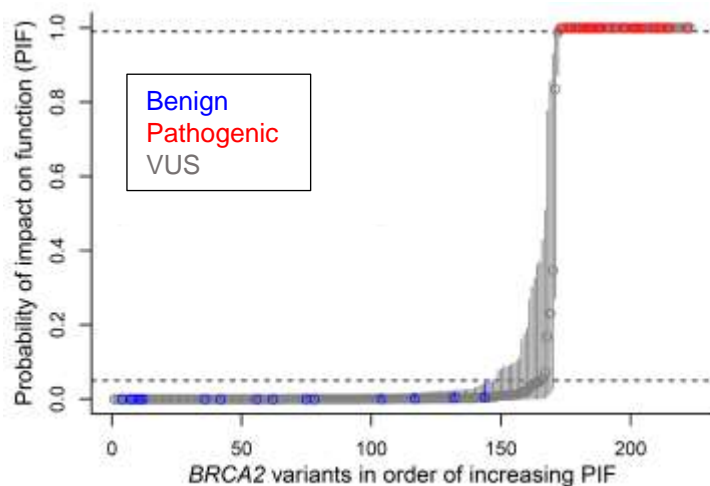


Olaparib

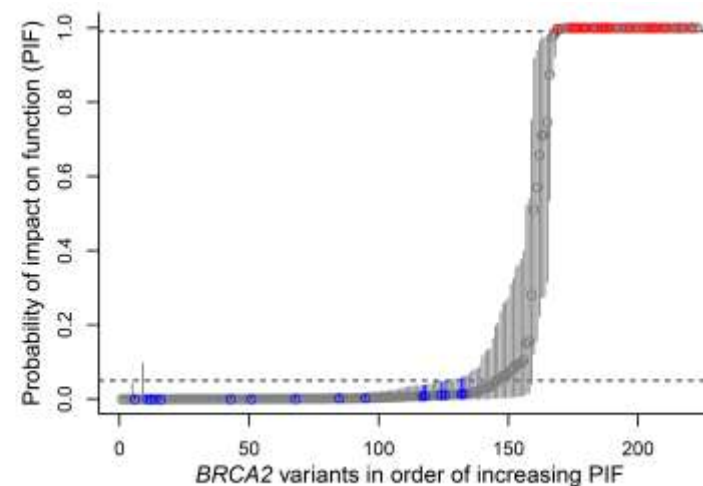


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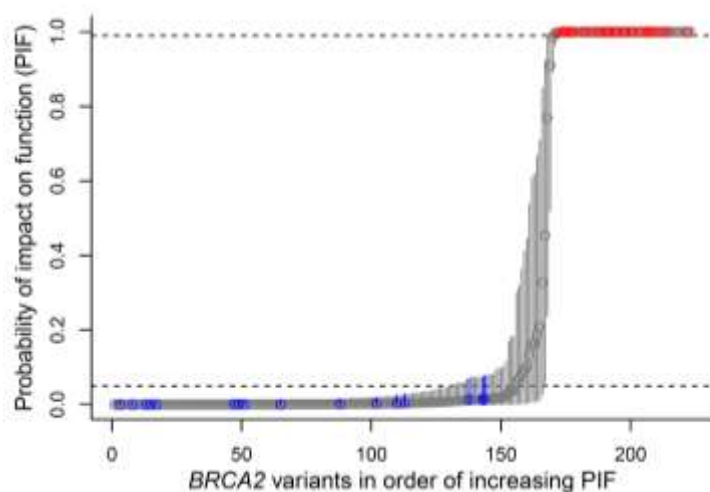
HAT



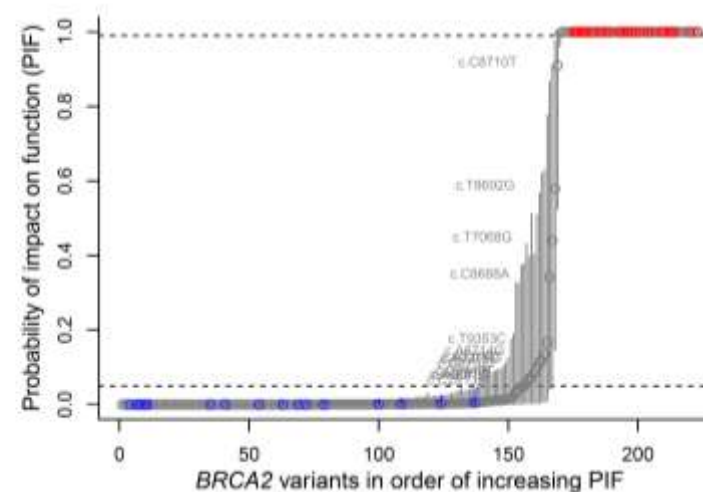
Cisplatin



Olaparib



HAT +  
Cisplatin +  
Olaparib

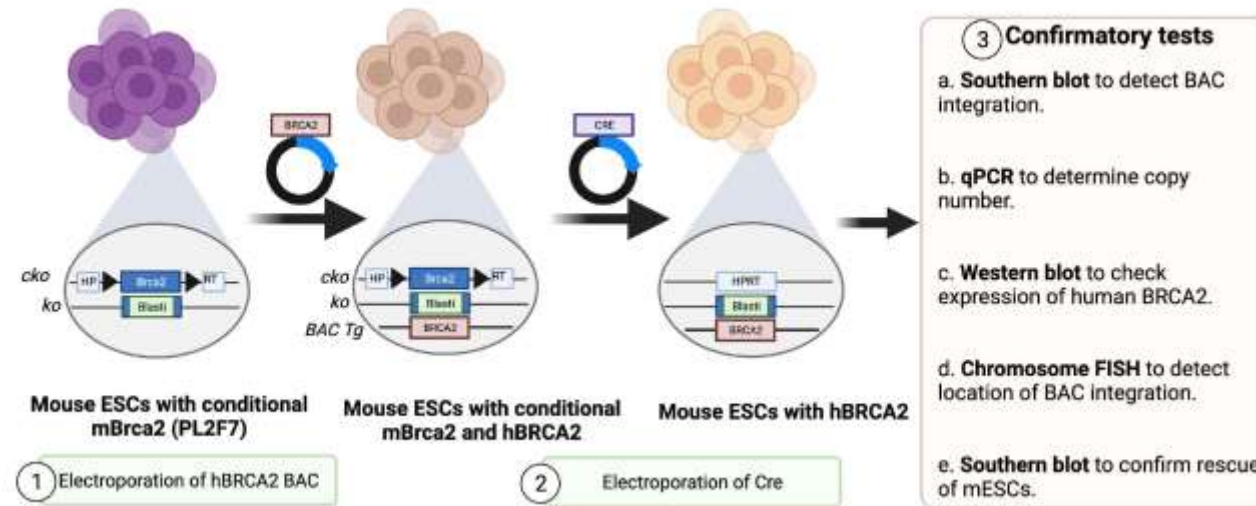


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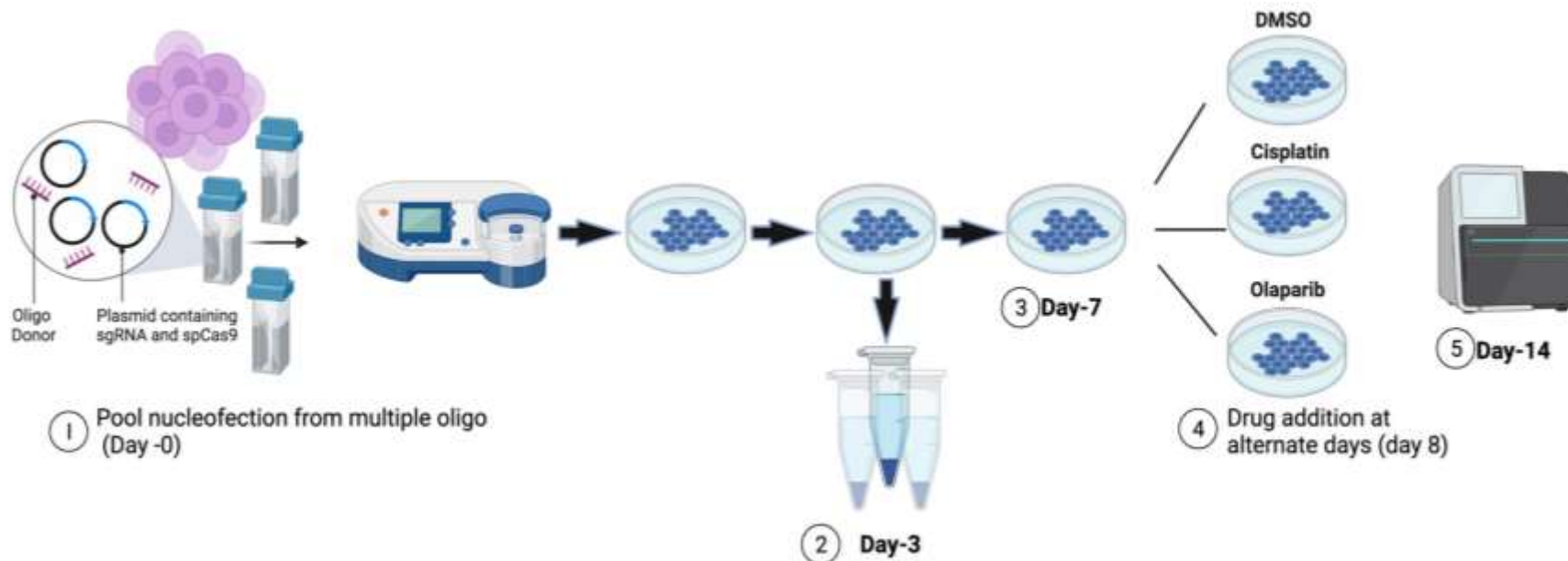
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But a new experimental technology required a different statistical approach

# The new data (N = 599): an advanced methodology



Essential  
aspect:  
CRISPR  
technology!!



# The new data (N = 599): an advanced methodology

On the **new** data set, the calculated PIFs were “not binary enough...”  
(i.e., not meeting the stringent classification thresholds of  $\text{PIF} \leq 0.05$  and  $\text{PIF} > 0.99$ )

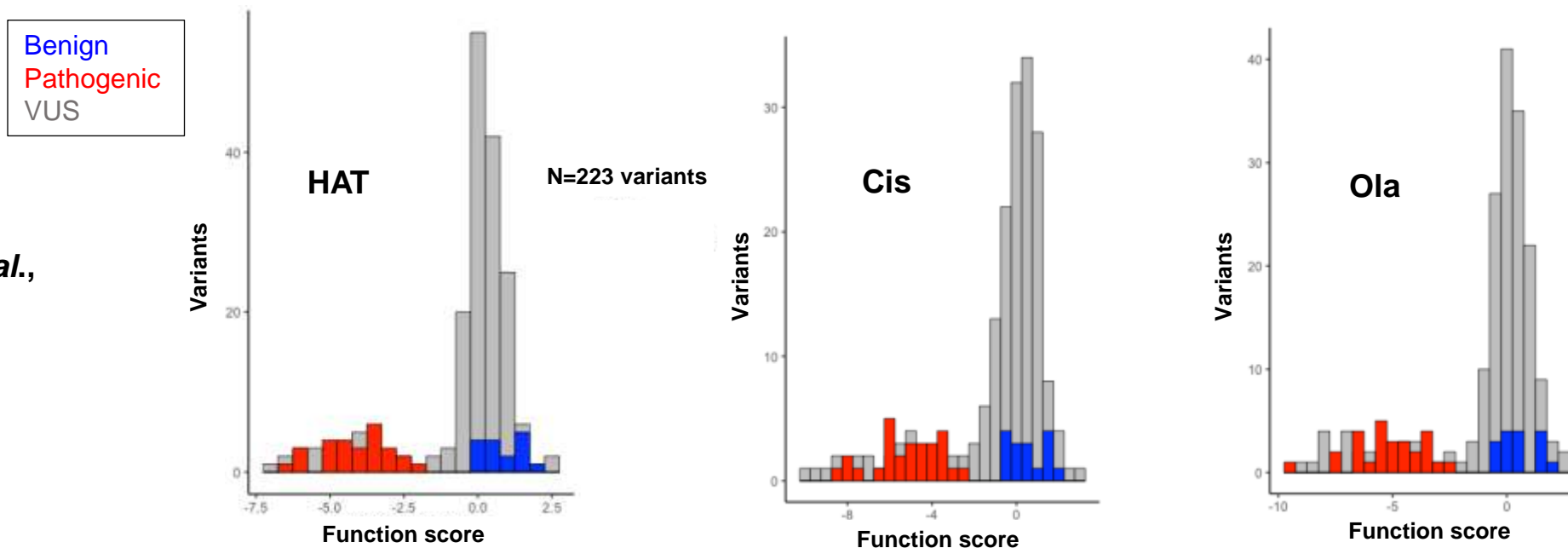
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But WHY ??



# Apparent reason: insufficient distribution separation

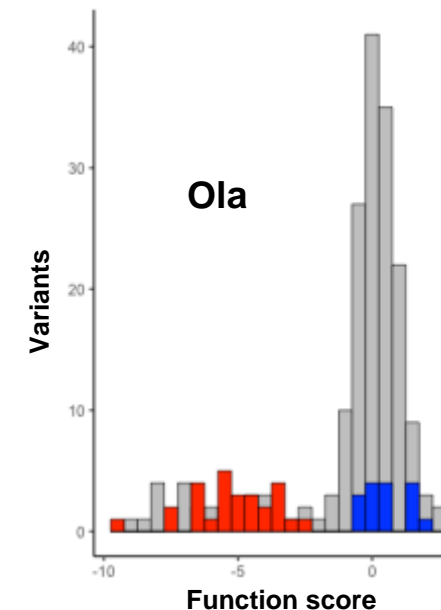
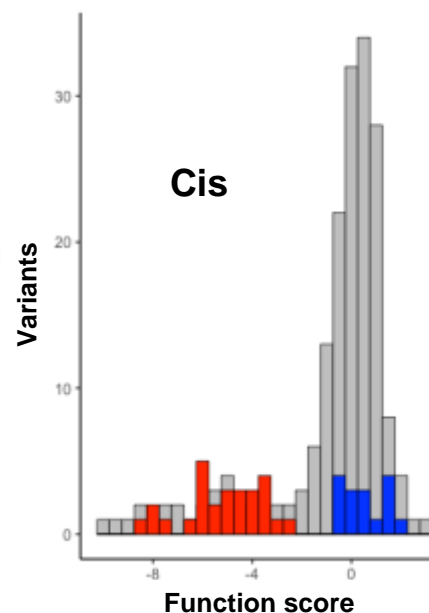
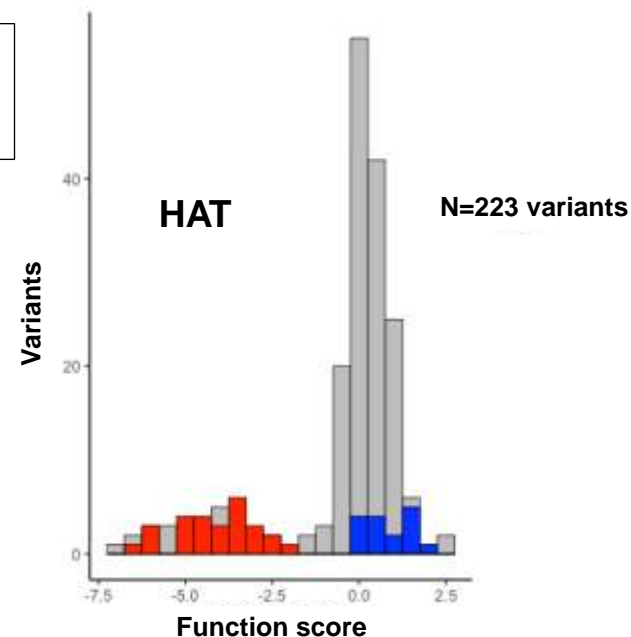
Biswas, Mitrophanov *et al.*,  
*Cell Rep Methods* 2023



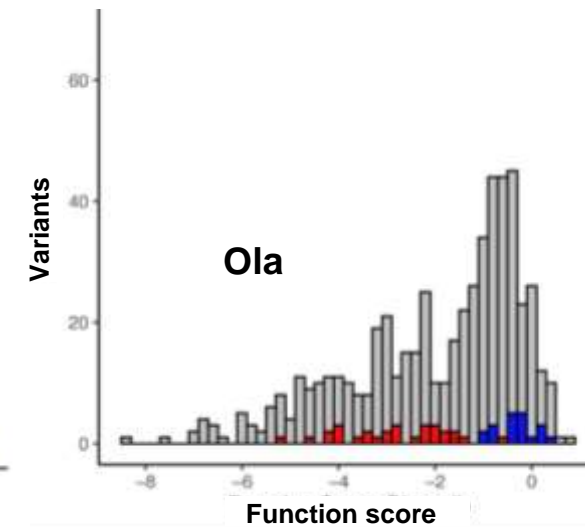
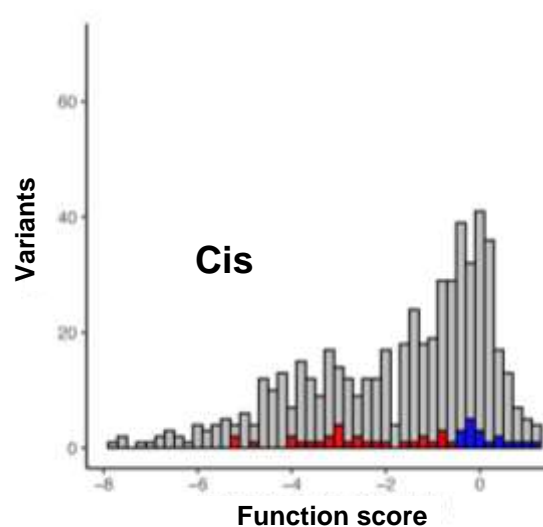
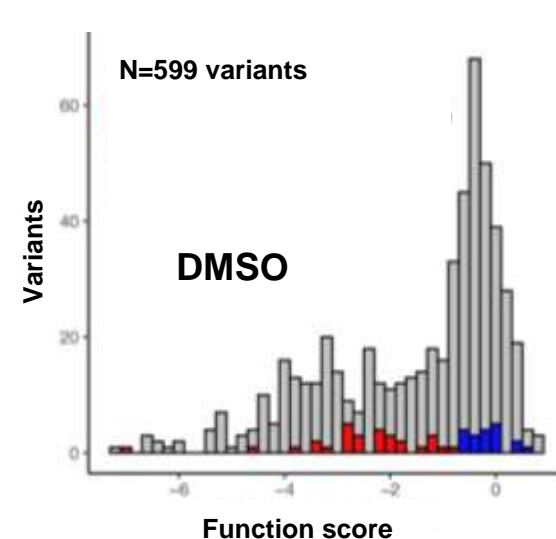
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Benign  
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VUS

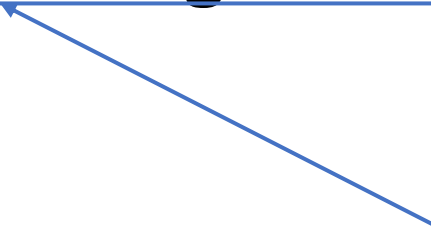
Biswas, Mitrophanov *et al.*,  
*Cell Rep Methods* 2023



Sahu, Sullivan, Mitrophanov *et al.*,  
*PLOS Genet* 2023



# The probit regression model



Just like logistic (=logit) regression, only with a different link function instead of log-odds

The standard supervised-learning approach !!

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- $N = 599$  *BRCA2* variants;  $N_b = 21$  labeled benign and  $N_p = 29$  labeled pathogenic (the rest,  $N_u$ , are VUS = variants of uncertain significance)
- 3 numerical variables: **DMSO**, **Cis**, and **Ola** (function scores), with values for every *BRCA2* variant

- PIF formulas for each *BRCA2* variant from classic probit regression:

**Full:**  $\text{probit}(PIF_i) = b_0 + b_1 DMSO_i + b_2 Cis_i + b_3 Ola_i$

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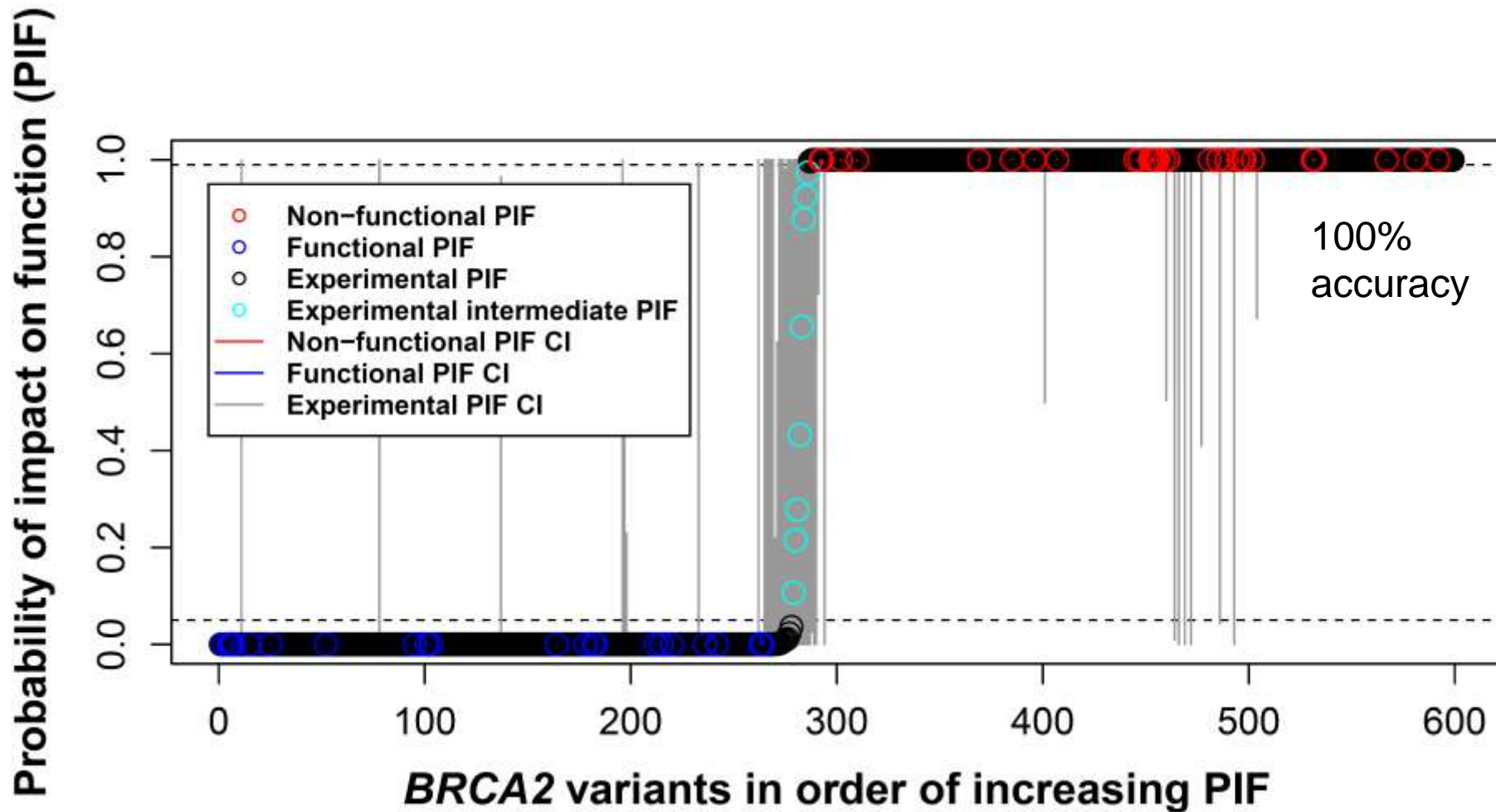
**Alternatives:**  $\text{probit}(PIF_i) = b_0 + b_1 DMSO_i$

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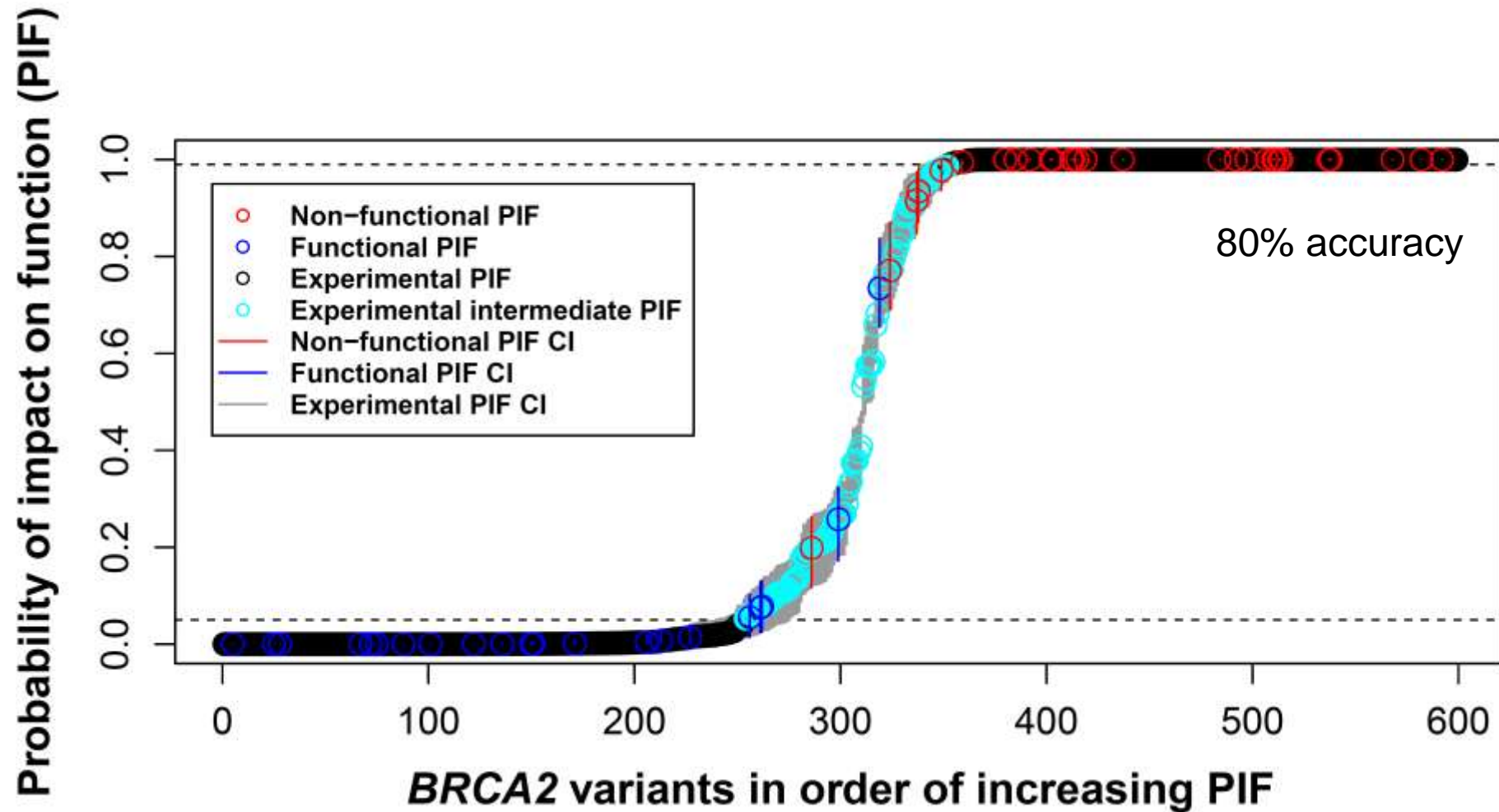
$$\text{probit}(PIF_i) = b_0 + b_1 Ola_i$$

**Validation approaches:** cross-validation (accuracy, sensitivity, specificity), information from diverse sources

# PIFs for the full (DMSO + Cisplatin + Olaparib) model

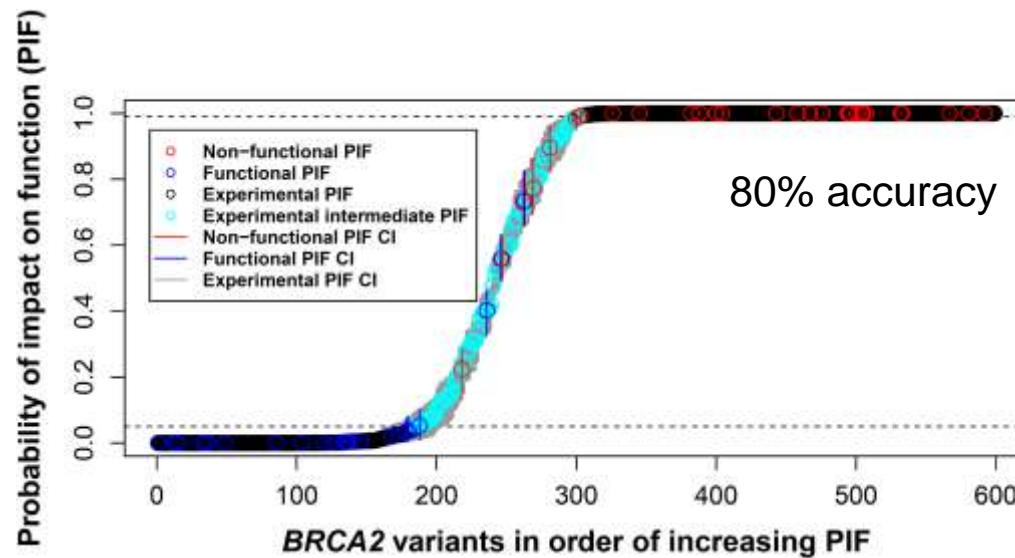


# PIFs for the DMSO model

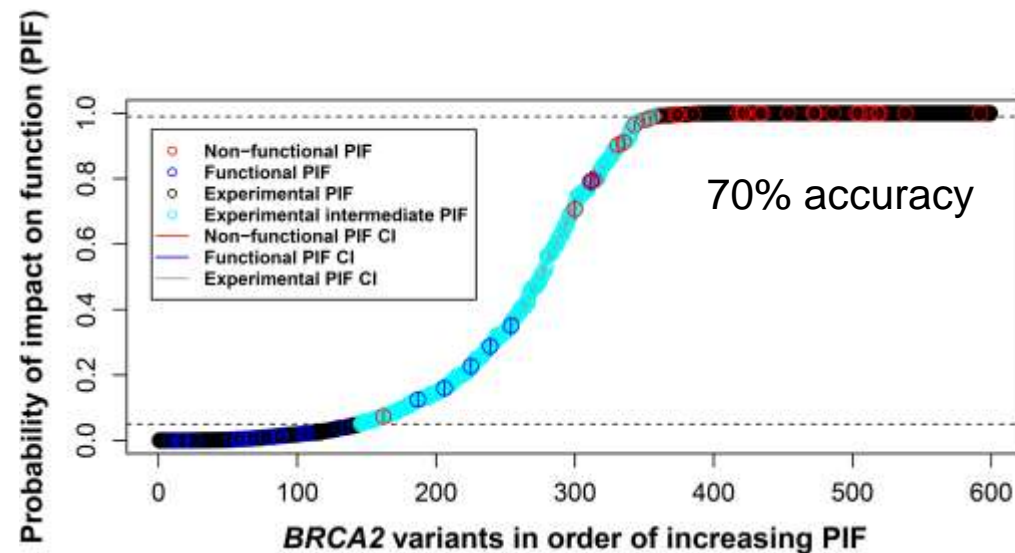


# PIFs for the Cisplatin and Olaparib models

Cisplatin



Olaparib



# Full probit-regression model: cross-validation results

Accuracy (K = 5, 10, 50): **94%**, **92%**, and **92%**

<Sensitivity, Specificity> (K = 5, 10, 50):	< <b>92.5%</b> , <b>93.3%</b> >
	< <b>91.7%</b> , <b>87.5%</b> >
	< <b>93.1%</b> , <b>90.5%</b> >

Could we do better? Great question for future research!!

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# Summary

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- Predicted the pathogenicity of hundreds of *BRCA2* variants of uncertain significance
- Performance of a particular PIF-calculation method strongly depends on the statistical distributions of the data
- Accurate and robust out-of-distribution analysis (i.e., broad generalization capability) appears to be a challenge in PIF calculation from functional-assay data



## Acknowledgements

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- Kajal Biswas, PhD (NCI)
- Sounak Sahu, PhD (NCI)

*QUESTIONS?*