

## UNIVERSITÀ DEGLI STUDI DI GENOVA



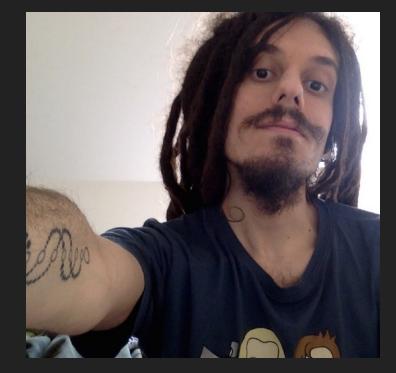
# PALLADIO: A PARALLEL FRAMEWORK FOR ROBUST VARIABLE SELECTION IN HIGH-DIMENSIONAL DATA

## Dipartimento di Informatica, Bioingegneria, Robotica e Ingegneria dei Sistemi



## UNIVERSITÀ **DEGLI STUDI DI GENOVA**





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# http://slipguru.unige.it/

# SUMMARY

Background: supervised learning and variable selection Framework description Validation on synthetic datasets Conclusions and future works

# BACKGROUND

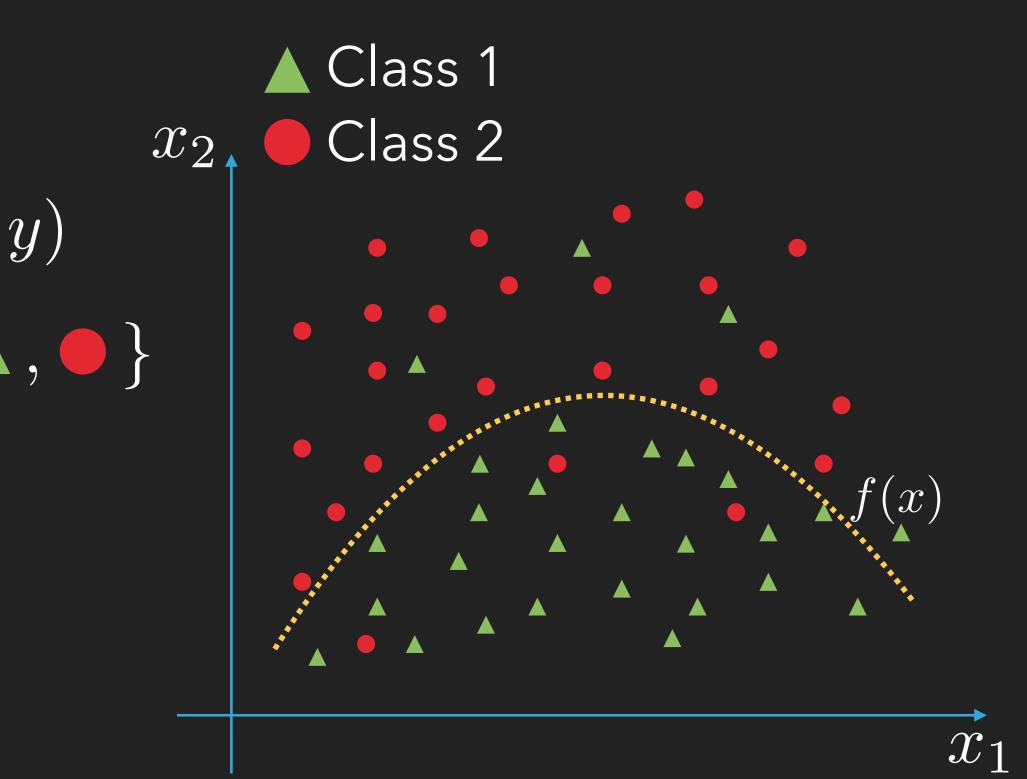


# LEARNING FROM EXAMPLES

Examples: pairs of the form  $(\mathbf{x}, y)$ e.g.  $\mathbf{x} = [x_1, x_2]$  and  $y \in \{ \blacktriangle, \bullet \}$ 

Goal: infer function f such that  $f(\mathbf{x}) \sim y$ 

More generally:  $\mathbf{x} \in \mathbb{R}^d$ 



# **VARIABLE SELECTION**

The process of identifying the subset of relevant variables

# ASSUMPTION

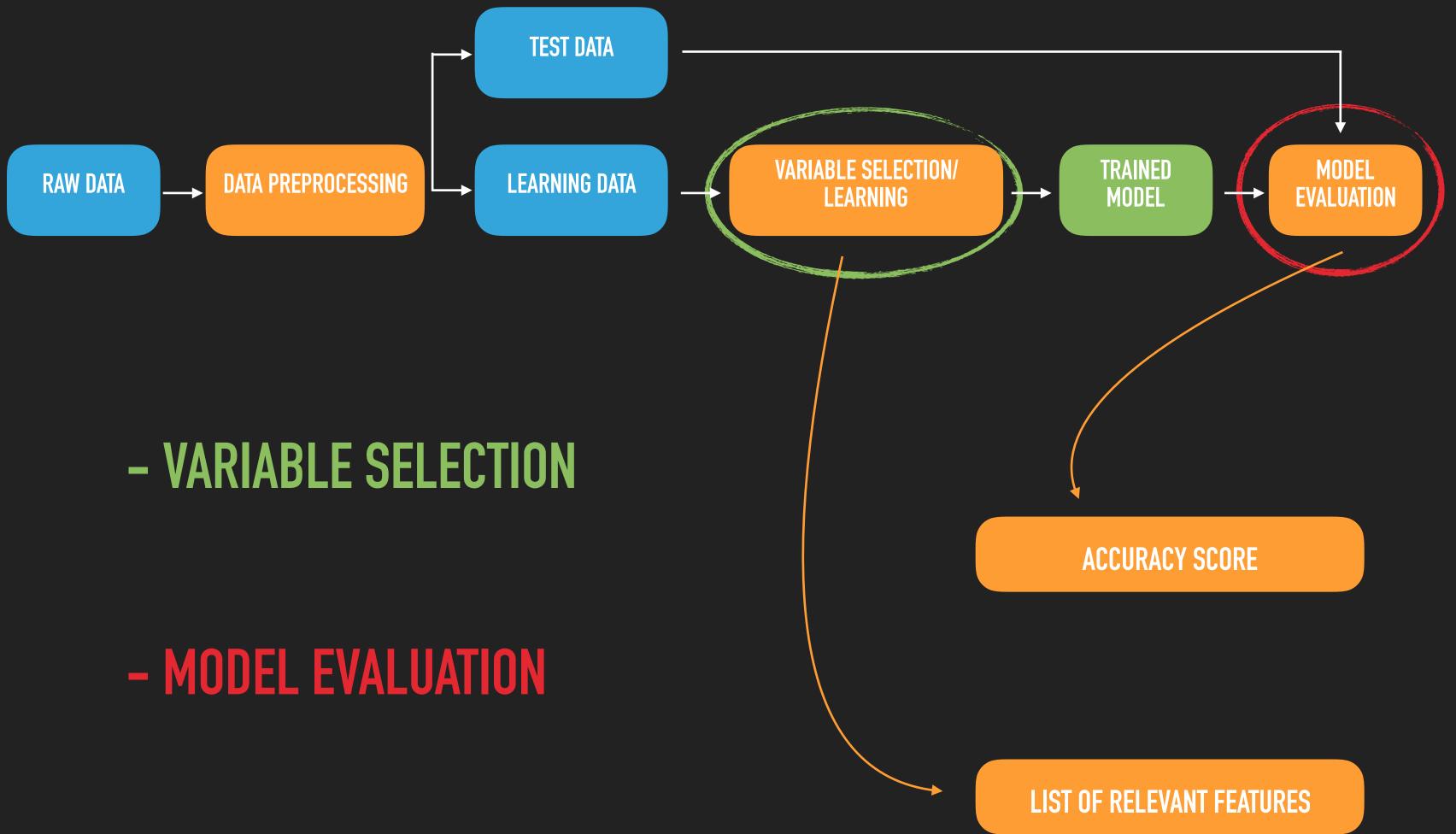
Not all variables are relevant for the problem

# PURPOSE

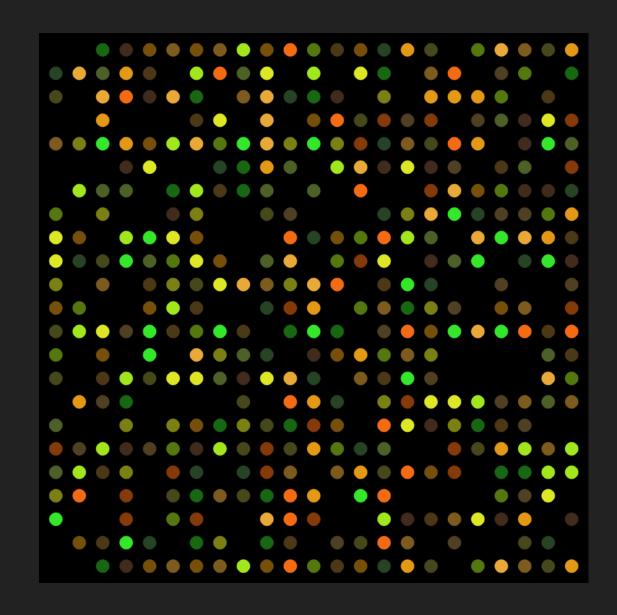
Reduce computational time

Enhance interpretability

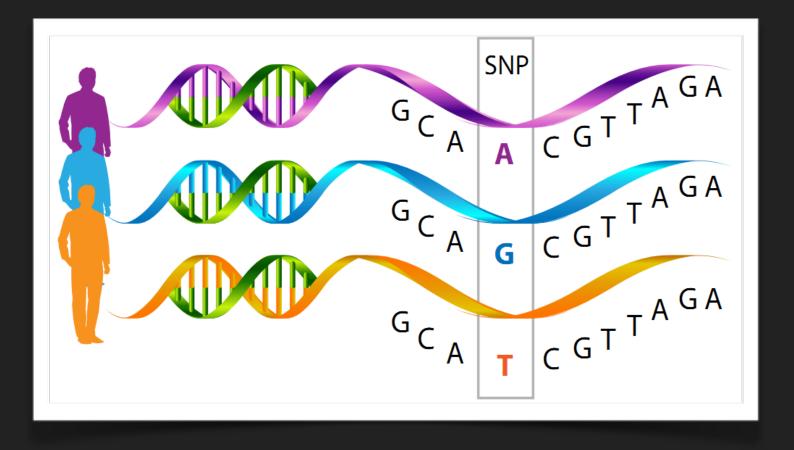
# THE LEARNING PIPELINE



# EXTREME CASES: $n \ll d$ , WEAK CORRELATION



Few examples (10<sup>2</sup>), high dimensionality (10<sup>4</sup> - 10<sup>6</sup>) Input and output are weakly correlated



- Classification accuracy close to chance

## A PARALLEL FRAMEWORK FOR ROBUST VARIABLE SELECTION IN HIGH-DIMENSIONAL DATA

# PAL LAD

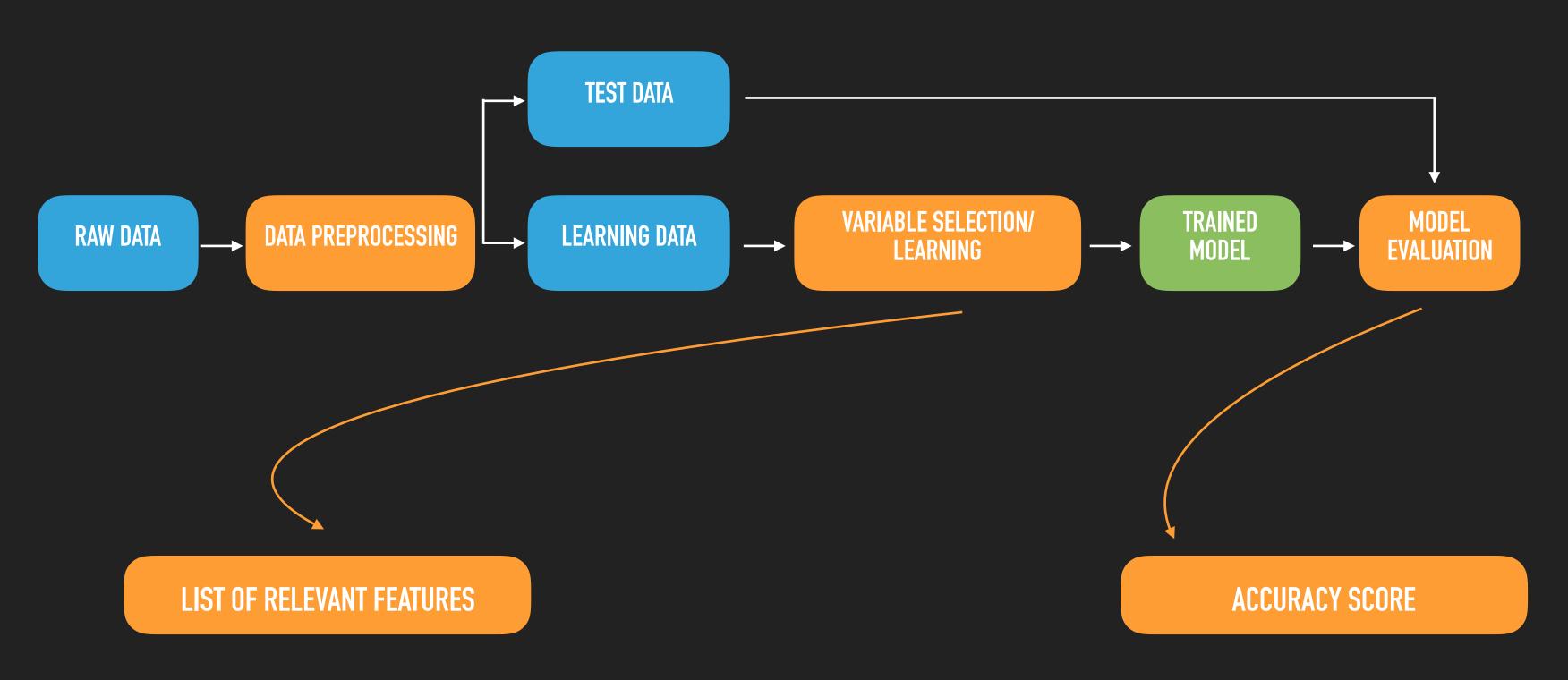




## - Select a subset of relevant variables

## - Provide a measure of the reliability of the results

# SCHEMA



## <u>One</u> accuracy score, <u>one</u> list of variables



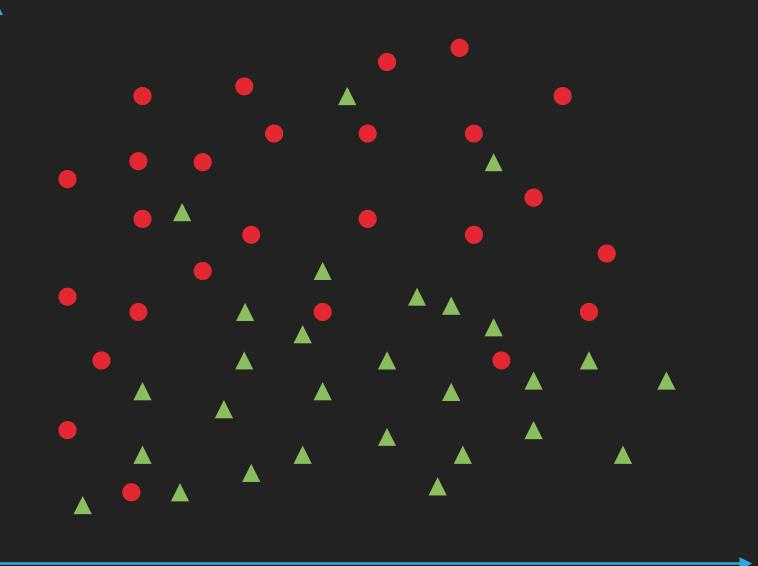
# Is it good? (chance is 50%) Does it depend on the split?

Accuracy = 54%

Repeat the experiments many times (100)

Resample learning and test set with MCCV

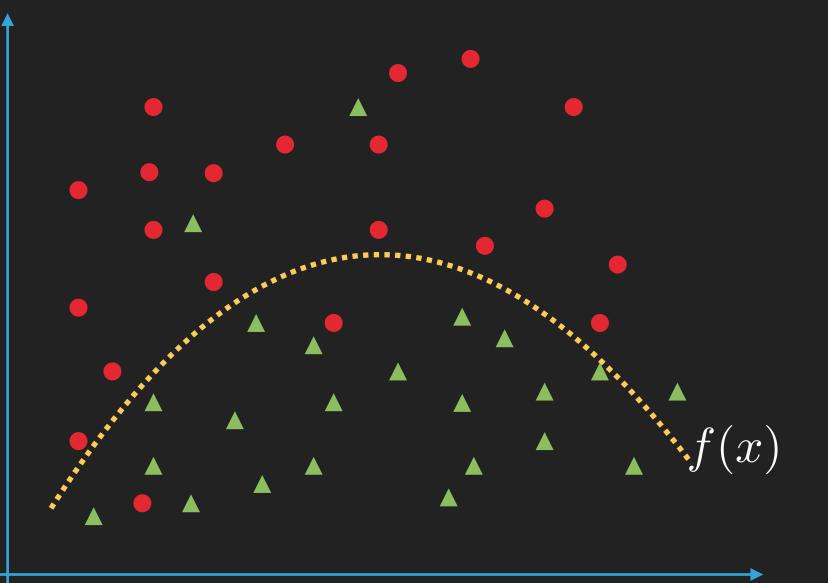
### **EXPERIMENT 1**



Repeat the experiments many times (100)

Resample learning and test set with MCCV

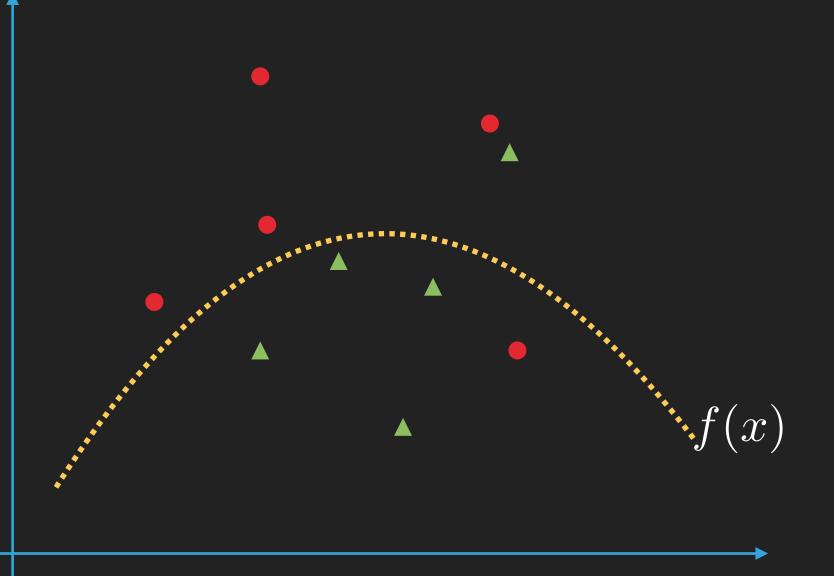
**EXPERIMENT 1: LEARNING SET** 



Repeat the experiments many times (100)

Resample learning and test set with MCCV

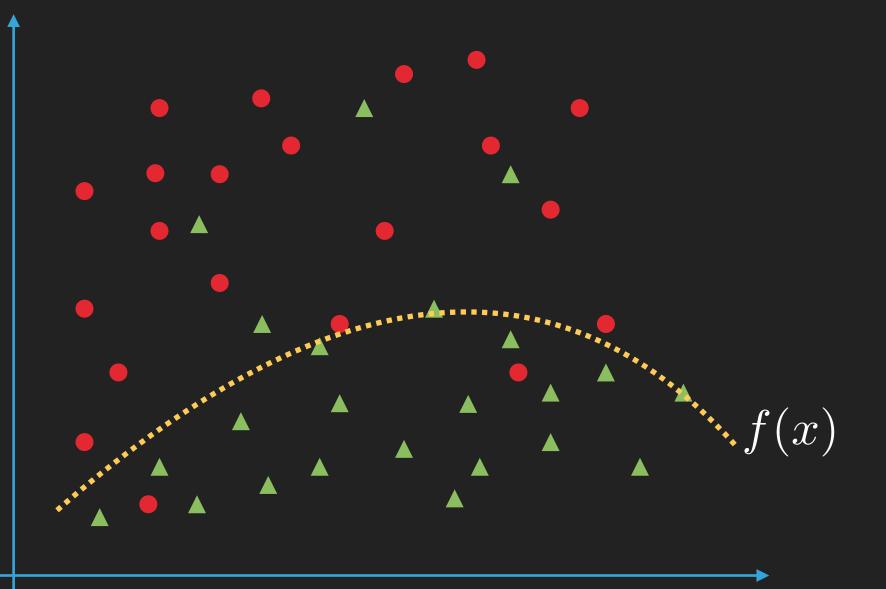
**EXPERIMENT 1: TEST SET** 



Repeat the experiments many times (100)

Resample learning and test set with MCCV

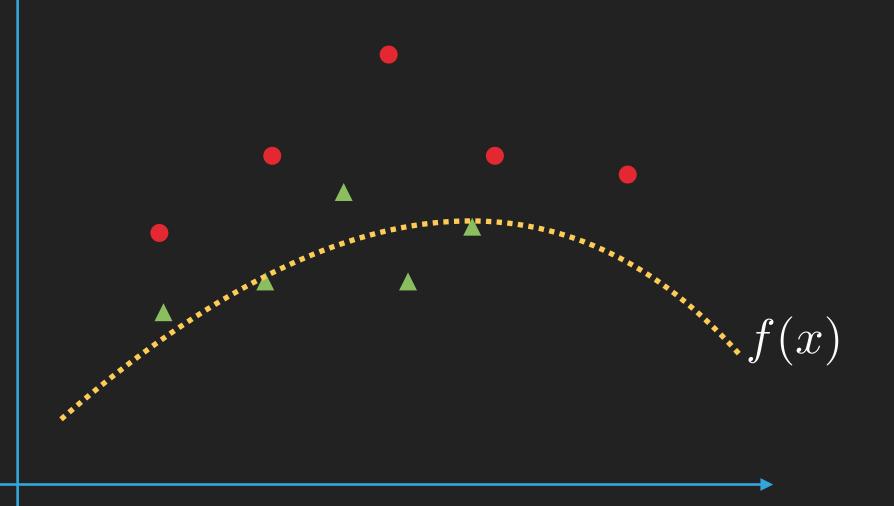
**EXPERIMENT 2: LEARNING SET** 



Repeat the experiments many times (100)

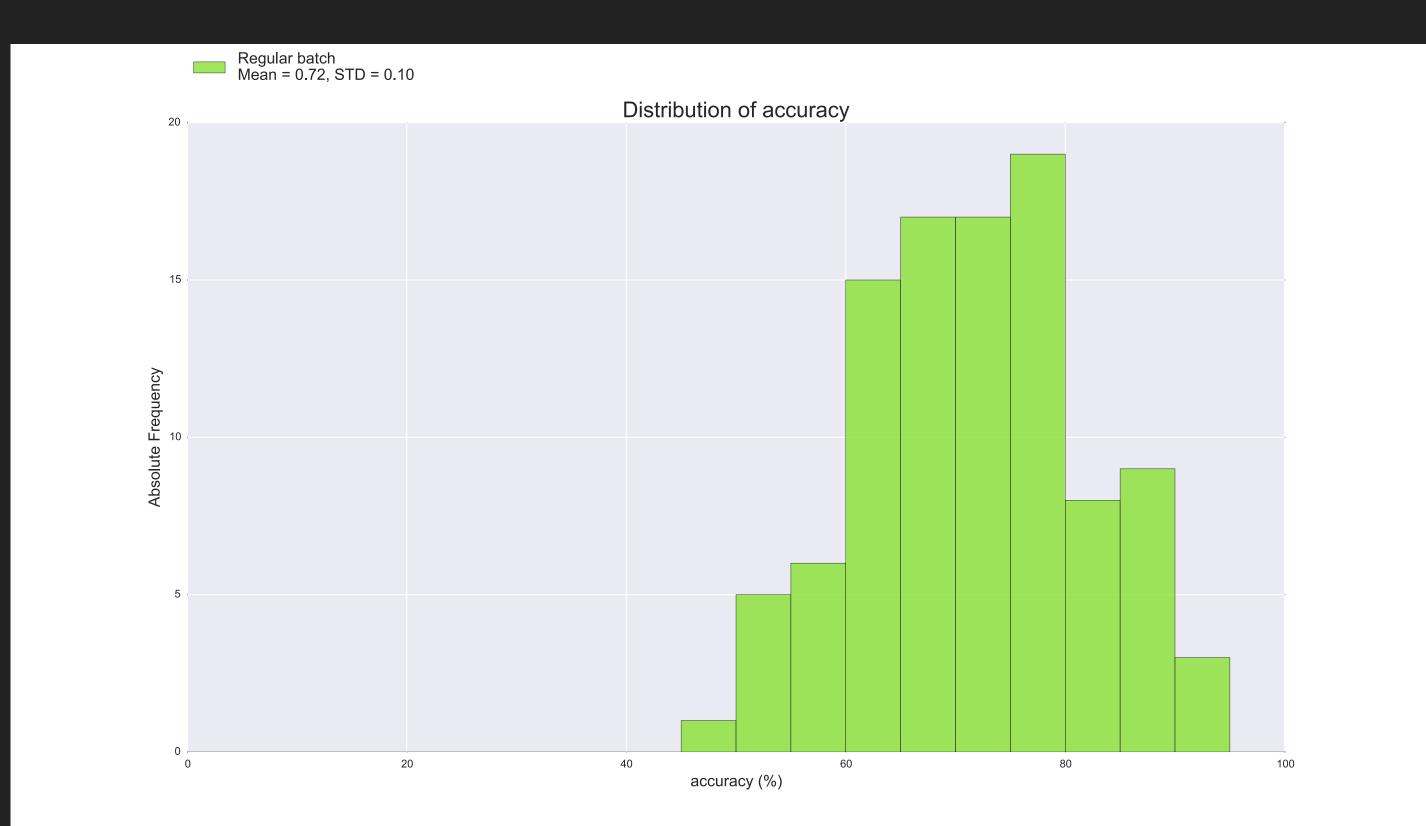
Resample learning and test set with MCCV

**EXPERIMENT 2: TEST SET** 



Repeat the experiments many times (100) 

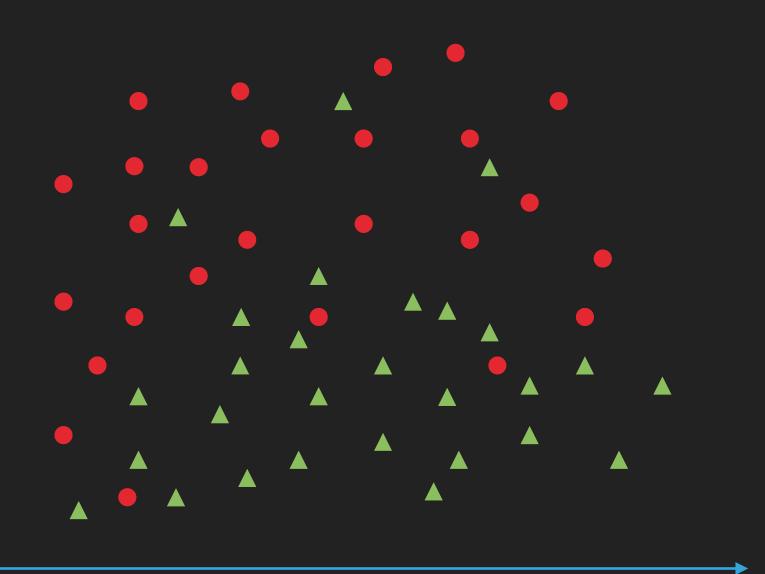
## Resample learning and test set with MCCV



Permutation test 

Labels in the learning set are shuffled

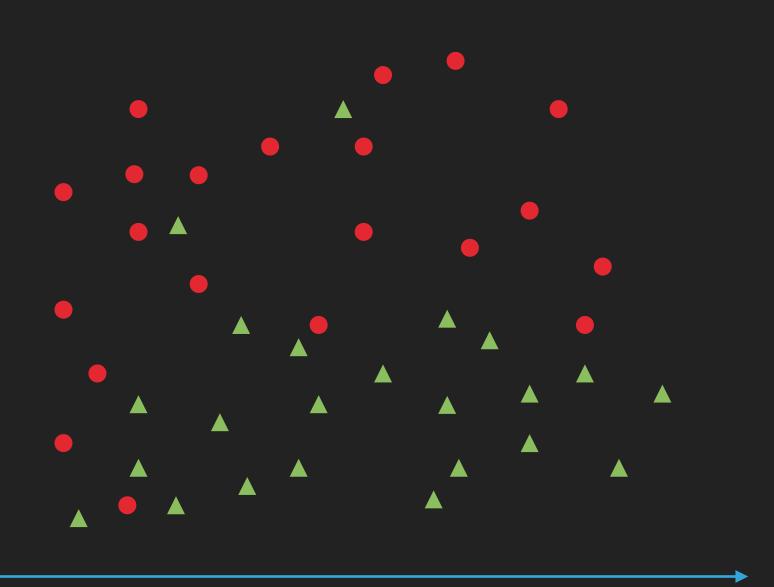
### **EXPERIMENT 1**



Permutation test 

Labels in the learning set are shuffled

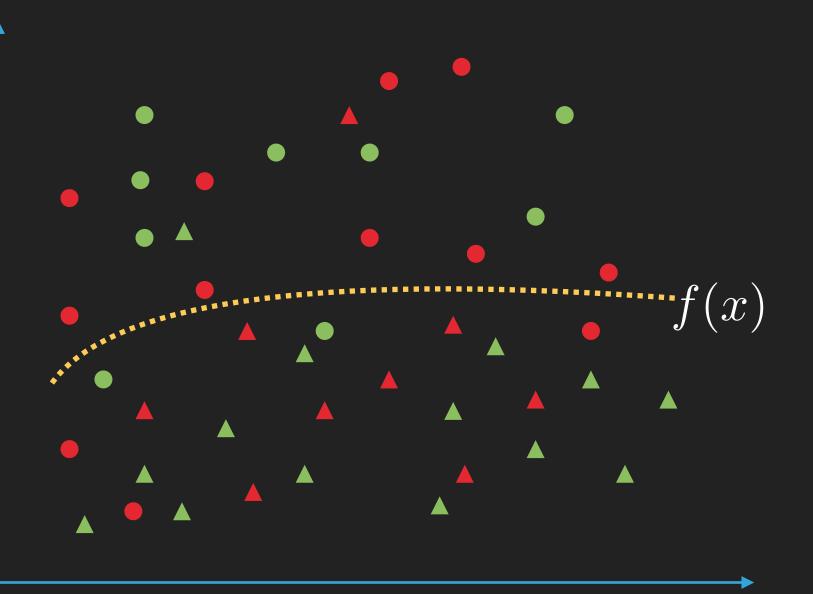
**EXPERIMENT 1: LEARNING SET** 



Permutation test 

Labels in the learning set are shuffled

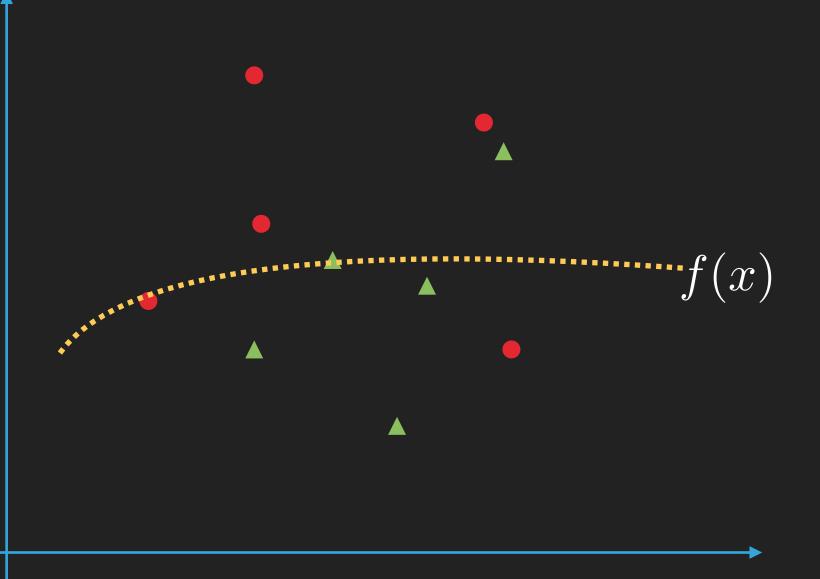
**EXPERIMENT 1: LEARNING SET** 



Permutation test

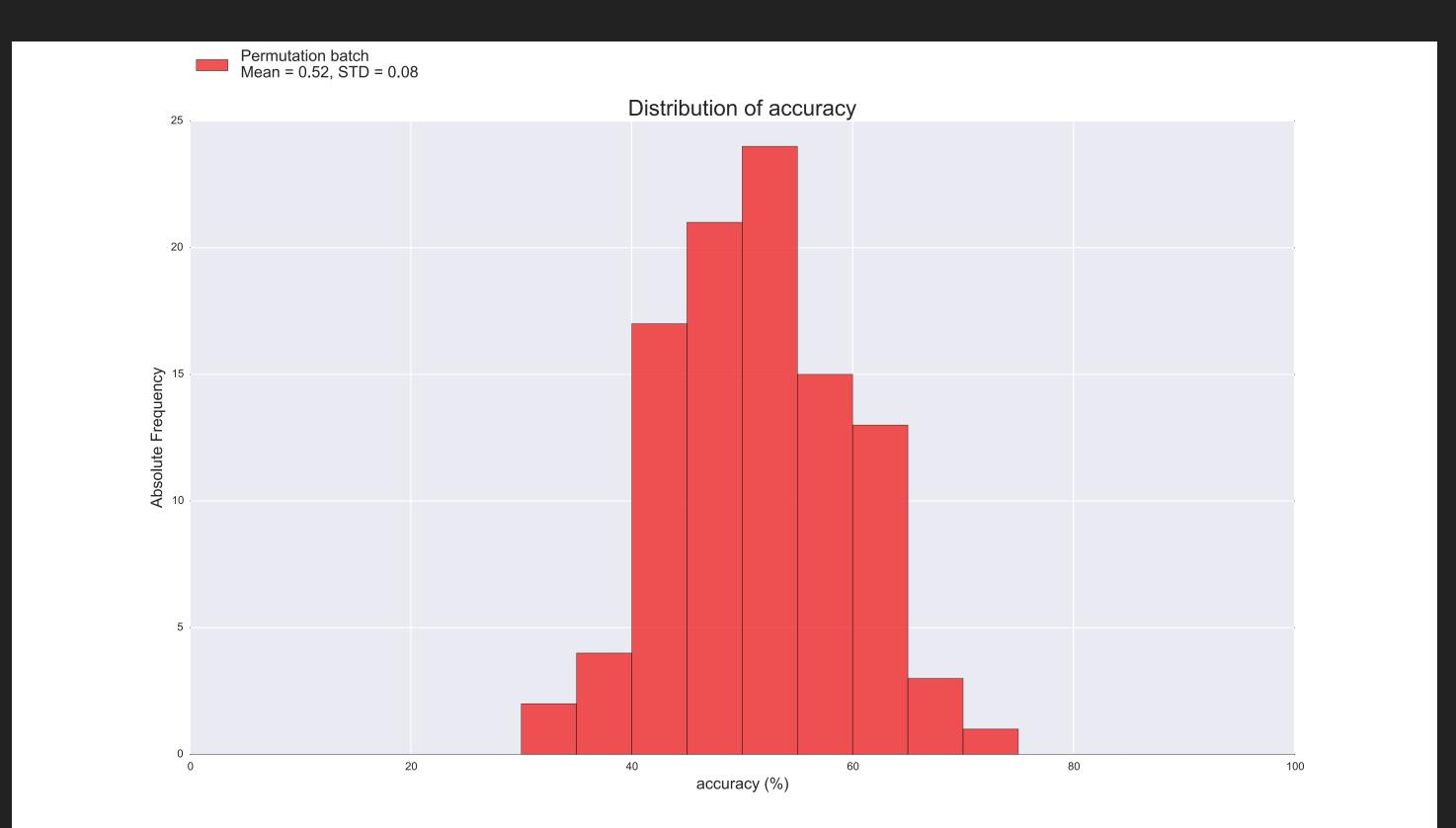
Labels in the learning set are shuffled

**EXPERIMENT 1: TEST SET** 

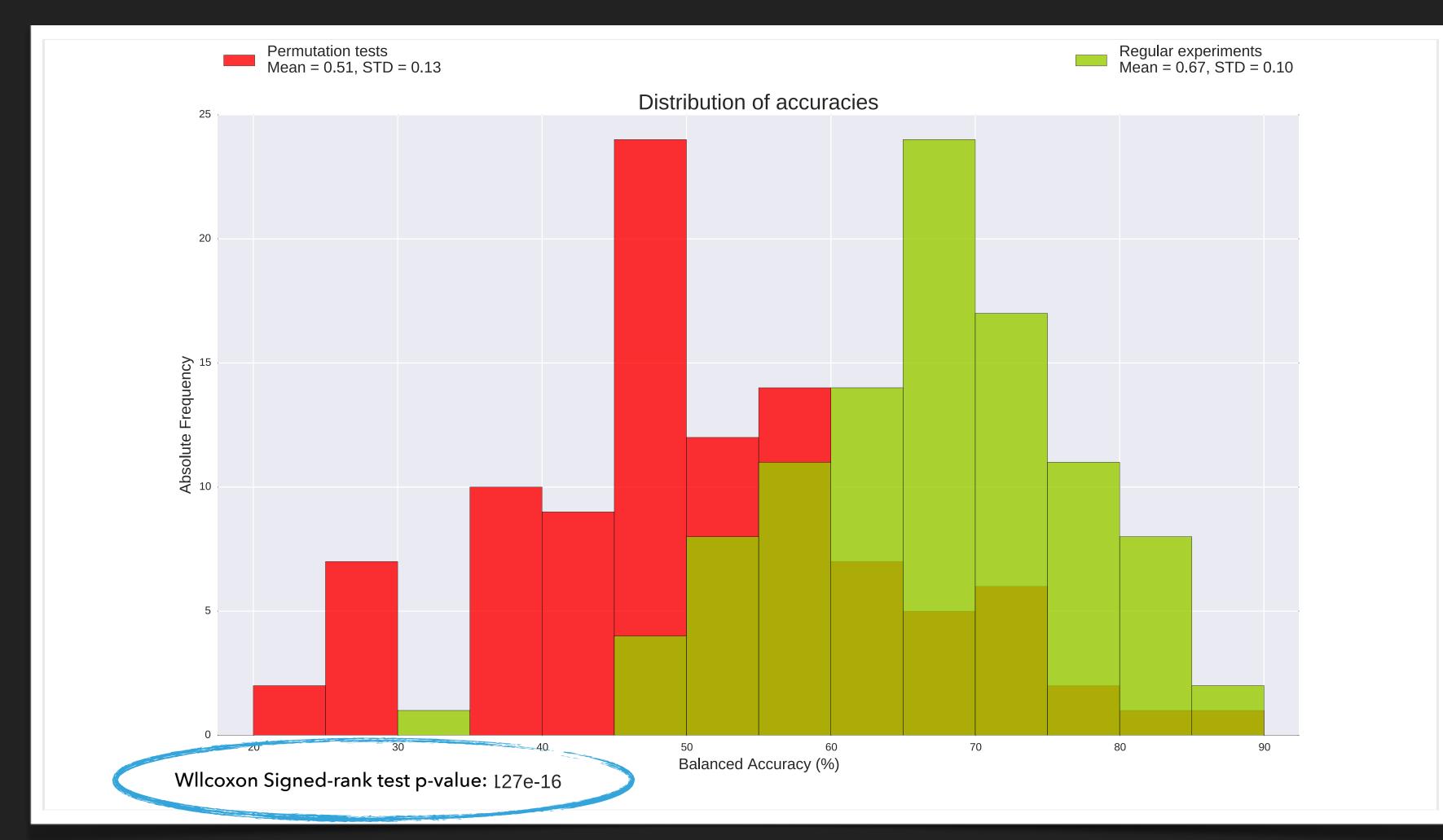


## Permutation test

## Labels in the learning set are shuffled



# **RESULTS – DISTRIBUTION OF ACCURACIES**



# **RESULTS – VARIABLES SELECTION FREQUENCIES**



- VAR #4, VAR #8, VAR #71, ...
- VAR #4, VAR #29, VAR #17, ...
- VAR #3, VAR #78, VAR #2, ...
- VAR #4, VAR #17, VAR #31, ...

# **RESULTS – VARIABLES SELECTION FREQUENCIES**

VAR #4 VAR #7 VAR #29 VAR #17  $\bullet$   $\bullet$   $\bullet$ VAR #78

## VARIABLE FREQUENCY

97% 91% 83% 78%  $\bullet \bullet \bullet$ 12%

# WORKLOAD DISTRIBUTION

MPI is used to distribute jobs in a cluster





••• Experiment #20 Experiment #20

• • •



Experiment #21 Experiment #21 Experiment #22 Experiment #22

Experiment #40 Experiment #40

• • •





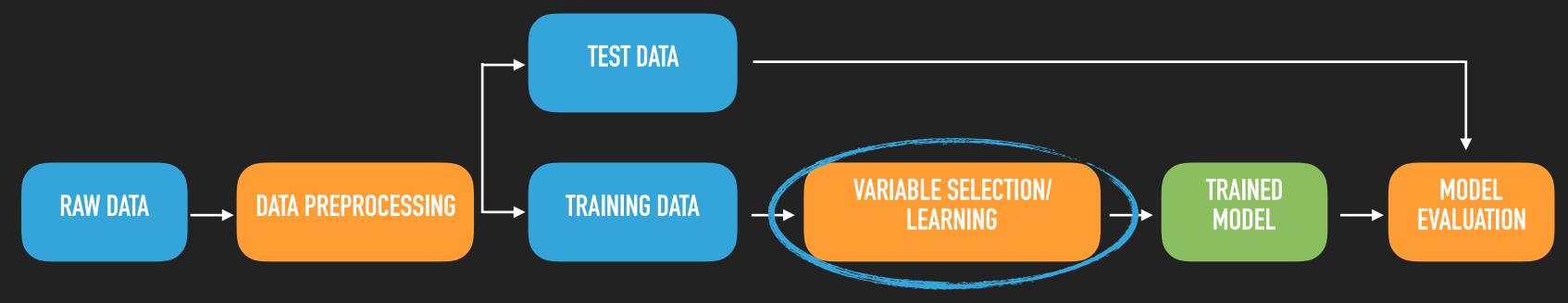
Experiment #81 Experiment #81 Experiment #82 Experiment #82

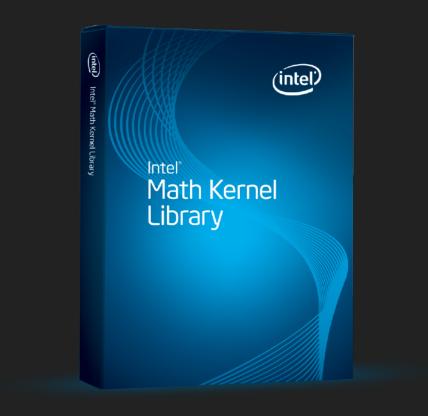
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Experiment #100 Experiment #100

# MKL/CUBLAS ACCELERATION

Libraries for linear algebra







## **OUR MACHINES**



Intel® Xeon® CPU E5-2630 v3 8 cores 2.4 GHz 32 GB of RAM NVIDIA Quadro K2200

Two Intel® Xeon® CPUs E5-2630 v3 8 cores 2.4 GHz (each) 128 GB of RAM NVIDIA Tesla K40c

# VALIDATION ON Synthetic datasets

# **REAL VALUED DATASETS – DATA**

45 datasets of different sizes:  $50 \le n \le 1000$  $1000 \le d \le 500000$ Binary classification task The number of relevant variables was proportional to the data dimensionality (between 25 and 100 relevant variables)



# **SYNTHETIC DATASETS - ACCURACY RESULTS**

### Accuracy values for all 45 experiments

Accuracy											1.00
50	0.87	0.88	0.72	0.90	0.92	0.90	0.98	0.93	0.92		0.95
es $n$ 100	0.95	0.92	0.85	0.95	0.95	0.95	1.00	1.00	1.00		0.90
Number of samples $n$ 200	0.96	0.93	0.90	0.98	0.98	0.98	1.00	1.00	1.00		0.85
Num 500	0.96	0.96	0.95	0.99	1.00	0.99	1.00	1.00	1.00		0.80
1000	0.99	0.96	0.98	1.00	0.99	0.99	1.00	1.00	1.00		0.75
1000 2000 5000 10000 20000 50000 100000 200000 500000 Number of dimensions d											

# **SYNTHETIC DATASETS – VARIABLE SELECTION RESULTS**

### F1 Scores for all 45 experiments

F1												
50	0.70	0.54	0.56	0.45	0.46	0.48	0.23	0.25	0.21			0.90
Number of samples n1000500200100	0.59	0.59	0.78	0.79	0.75	0.73	0.72	0.68	0.59			0.75
	0.54	0.56	0.62	0.72	0.82	0.84	0.94	0.94	0.95			0.60
	0.43	0.42	0.46	0.59	0.65	0.72	0.87	0.89	0.98			0.45
	0.79	0.60	0.96	0.44	0.58	0.62	0.75	0.84	0.93			0.30
	1000	2000	5000	10000 Number	20000 of dime	50000 nsions d		200000	500000			

# **CPU VS GPU SPEEDUP**

50	0.32	0.35	0.41	0.49	0.54	0.72	0.87	0.97	1.05		1.50
ples $n$ <sup>100</sup>	0.61	0.59	0.63	0.77	0.86	1.36	1.47	1.51	1.60		1.25
Number of samples $n$ 200 200 100	0.80	0.82	0.85	0.99	1.59	1.72	1.71	1.69	1.65		1.00
Numb 500	1.24	1.18	1.28	1.64	1.64	1.67	1.66	1.73	1.73		0.75
1000	1.14	1.25	1.28	1.32	1.44	1.61	1.64	1.70	1.73		0.50
1000 2000 5000 10000 20000 50000 100000 200000 500000 Number of dimensions $d$											

# **CONCLUSIONS AND FUTURE WORK**

# CONCLUSIONS

- The framework allowed us to obtain clear results (either positive or negative) on both synthetic and real datasets
- The MPI implementation allows for the analysis of large datasets in a reasonable amount of time

# **FUTURE WORKS**

- Extension to the regression problems
  Inclusion of wrappers for more learning algorithms
  A different job distribution strategy (Master/Slave) for heterogeneous clusters
- Obtaining a single model through a final training step

# AKNOWLEDGEMENTS



# 

# THANKS

## HTTPS://GITHUB.COM/SLIPGURU/PALLADIO

# Matteo Barbieri, 2016