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# Engineering Fast Multilevel Support Vector Machines

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# ENGINEERING FAST MULTILEVEL SUPPORT VECTOR MACHINES

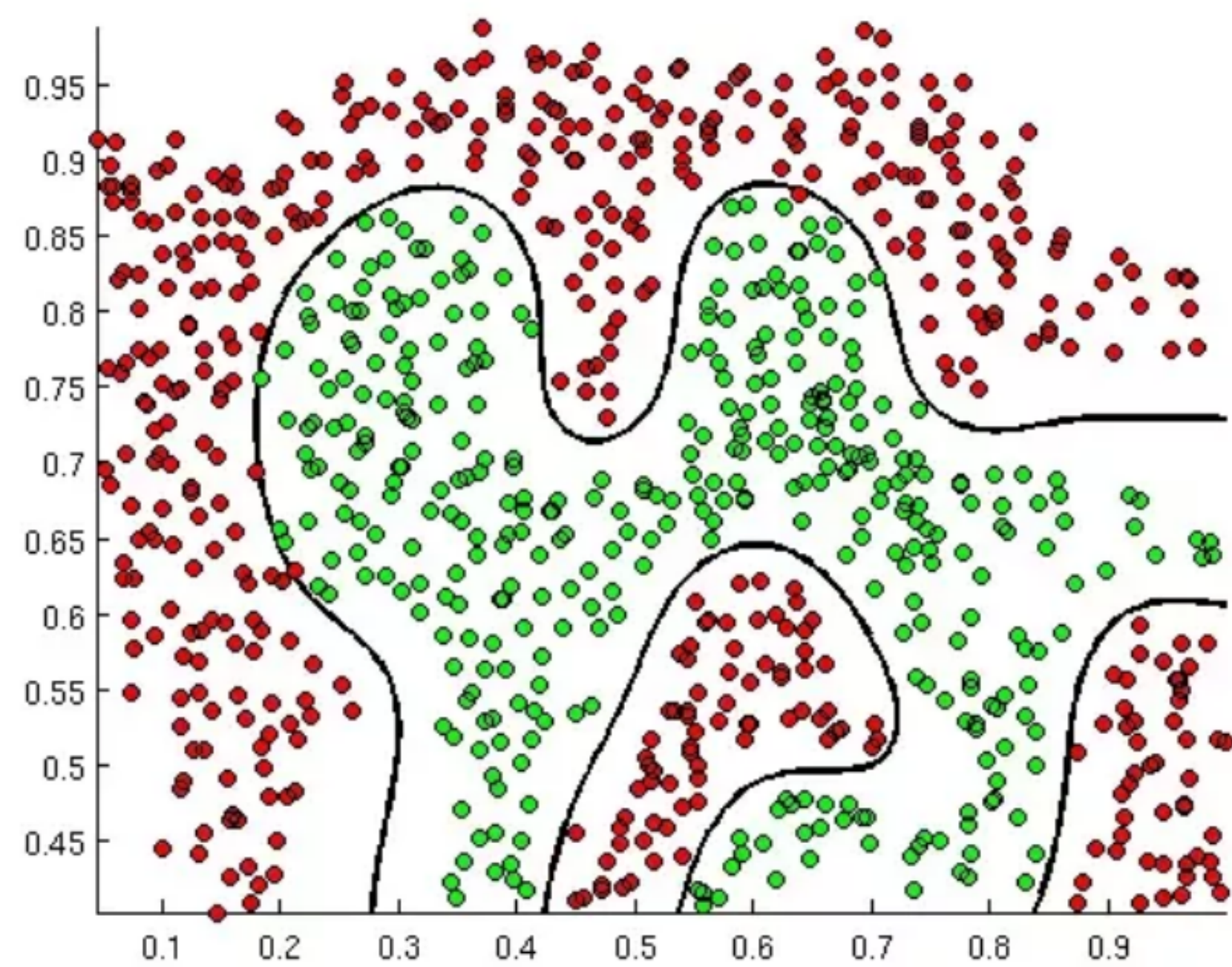
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## MOTIVATION

### Classification Problem:



- Find a function to separate data points
- Accurately predict the unseen data
- Advance techniques are perform better for complex data points

## MULTILEVEL SVM

- The problem: Solving large, hard, imbalanced data set **takes long time**
- Our solution: **Very fast solver with high quality**
- Source code: <https://github.com/esadr/mlsvm>

## GENERAL (W)SVM

- Data points  $\{(x_i, y_i)\}_{i=1}^l$
- Class labels  $(y_i)$  are  $-1, +1$
- Weighted SVM: The WSVM is an extension of the SVM for imbalanced classes:

$$\min \frac{1}{2} \|w\|^2 + C^+ \sum_{i \in C^+} \xi_i + C^- \sum_{j \in C^-} \xi_j \quad (1a)$$

$$\text{s.t. } y_i(w^T \phi(x_i) + b) \geq 1 - \xi_i \quad i = 1, \dots, l \quad (1b)$$

$$\xi_i \geq 0 \quad i = 1, \dots, l \quad (1c)$$

where the importance factors  $C^+$ , and  $C^-$  are associated with the positive, and negative classes respectively.

- The WSVM can be transformed into the Lagrangian dual and solved using the Kuhn-Tucker conditions.

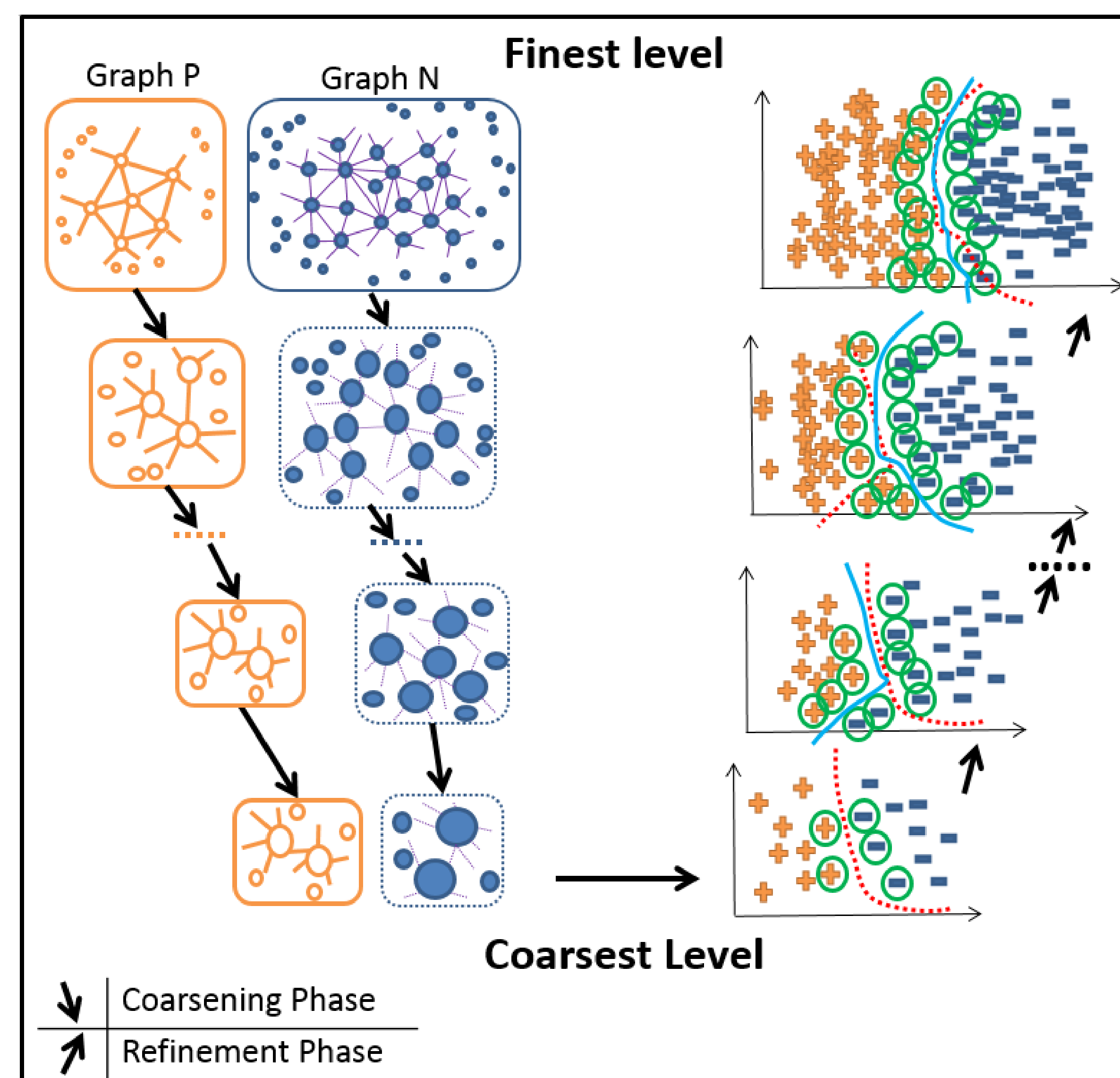
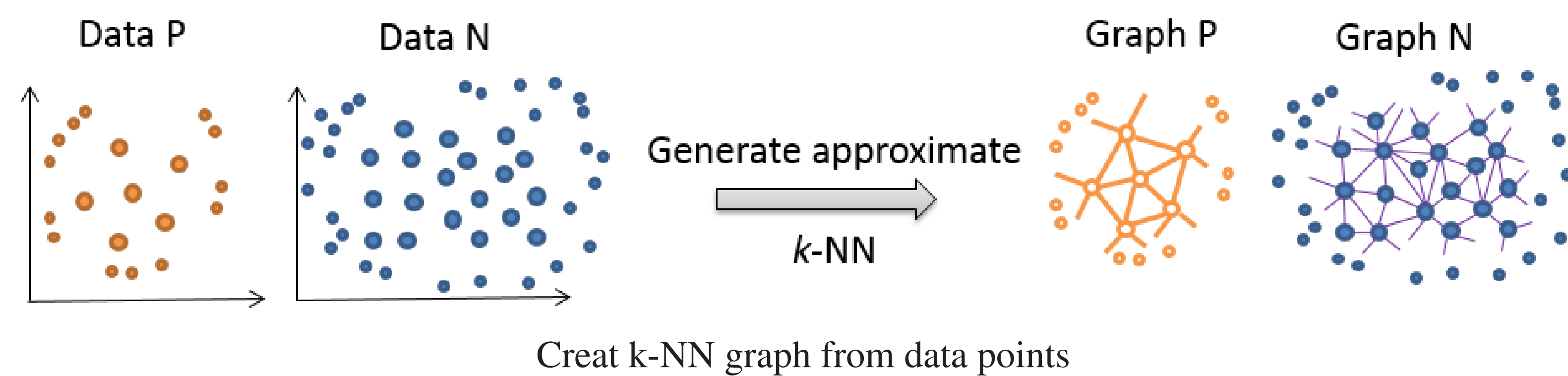
## REFERENCES

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- [3] Razzaghi, T., Safro, I., Ewing, J., Sadrfaridpour, E., and Scott, J., D. (2019). "Predictive Models for Bariatric Surgery Risks with Imbalanced Medical Datasets." Annals of Operations Research, <https://doi.org/10.1007/s10479-019-03156-8>.

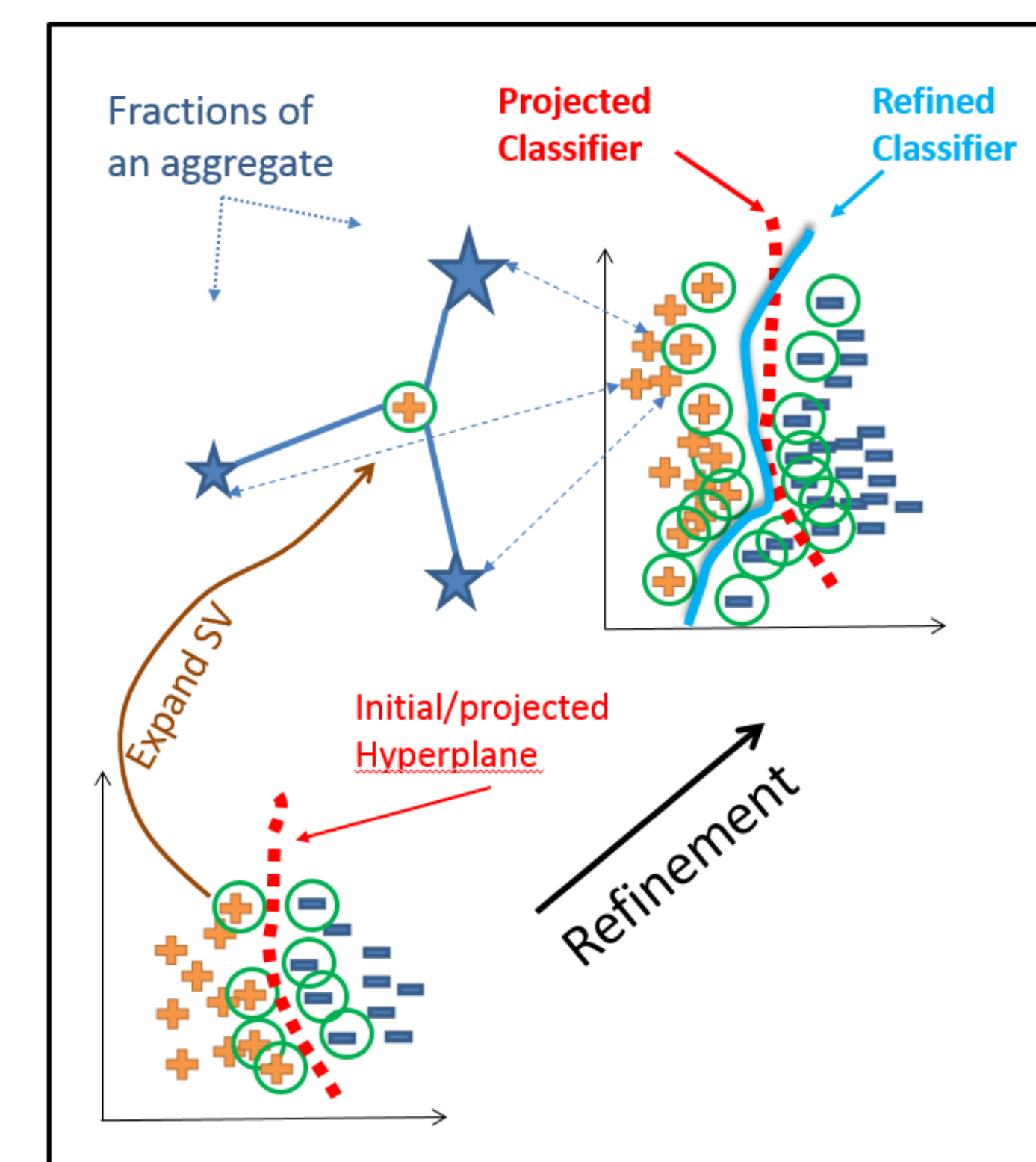
## MULTILEVEL SUPPORT VECTOR MACHINES

We propose a new class of multilevel (W)SVM algorithms that is based on the **Algebraic Multigrid framework (AMG)**.

- **Coarse Problem.** The classification problem is reformulated as *(Weighted) Support Vector* classification problem for a non-uniform AMG coarsening, i.e., the  $C^+/C^-$  classes are separated.
- **AMG Coarsening.** We construct aggregates of fractions of data points using the Galerkin-like operator from AMG applied on the Laplacian of approximated  $k$ -NN graph.
- **Coarse Aggregates.** The construction of the set of aggregates is guided by the principle that each fine point should be "strongly coupled" to the chosen aggregates.



(a) Overall Multilevel framework



(b) Adding SV's neighbors in a finer level

- **Refinement.** Add SVs and their neighbors in a finer level. In case of large training data, partition and choose closest pairwise partitions

## RESULTS

- Our multilevel WSVM are evaluated on binary classification benchmark data sets.
- Performance measure (G-mean) and Time are reported for comparison between classical WSVM and MLSVM for small data sets and between LibLinear and MLSVM for large data sets
- **Main achievement: Fast computational time and improved quality on complex data sets**

Name	Data set			Time (sec.)		G-mean	
	$r_{imb}$	$f$	Size	WSVM	MLSVM	WSVM	MLSVM
Advertisement	0.86	1558	3279	231	<b>213</b>	0.67	<b>0.91</b>
Buzz	0.80	77	140707	26026	<b>31</b>	0.89	<b>0.95</b>
Clean	0.85	166	6598	82	<b>5</b>	0.99	0.99
Cod-rna	0.67	8	59535	1857	<b>13</b>	<b>0.96</b>	0.94
Forest	0.98	54	581012	353210	<b>948</b>	<b>0.92</b>	0.88
Letter	0.96	16	20000	139	<b>30</b>	0.99	0.99
Nursery	0.67	8	12960	192	<b>2</b>	1.00	1.00
Ringnorm	0.50	20	7400	26	<b>2</b>	0.98	0.98
Twonorm	0.50	20	7400	28	<b>1</b>	0.98	0.98

Name	Data set			Time (sec.)		G-mean	
	$r_{imb}$	$f$	Size	LibLinear	MLSVM	LibLinear	MLSVM
SUSY	0.54	18	5M	1300	<b>1116</b>	0.68	<b>0.74</b>
MNIST	0.90	784	4M	2626	<b>17581</b>	0.60	<b>0.84</b>
HIGGS	0.53	28	11M	4406	<b>3283</b>	0.54	<b>0.62</b>

## ONGOING RESEARCH

- Develop the parallel version using MPI and OpenMP