Local Decomposition for Rare Class Analysis

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Outline

Why care about rare classes?

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Can we do better?

Linear classifiers and rare classes

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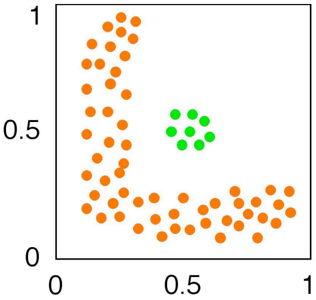
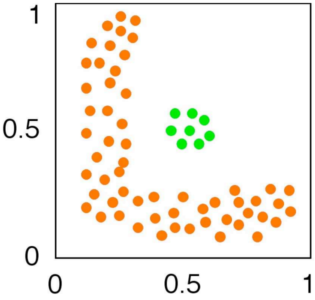
Yet nonlinearly separable data exacerbates the rare class problem.



COG (Classification using lOcal clusterinG)



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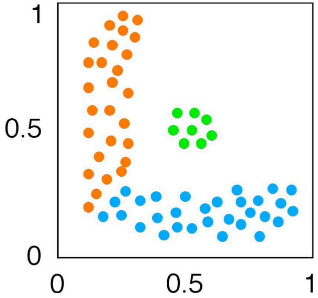

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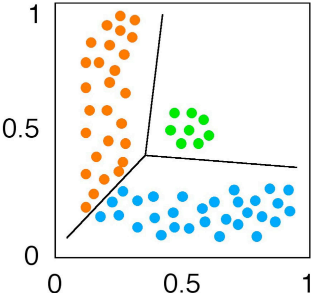

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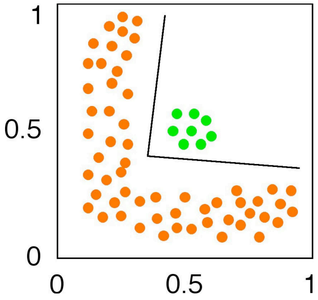

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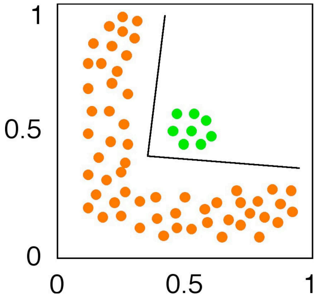

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The F measure

Recall:	Fraction of those *actually* in X that were placed there
Precision:	Fraction of those *placed* in X that were actually there

$$F = \frac{2 \cdot \mathrm{Recall} \cdot \mathrm{Precision}}{\mathrm{Recall} + \mathrm{Precision}}$$

Results

Pima (diabetes):

	SVM	COG(SVM)
rare	NA	0.373
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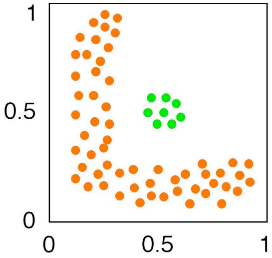
- The F-measure generally improves on small classes.

Comparisons

Two alternative approaches to rare classes:

- over-sampling; and
- under-sampling.



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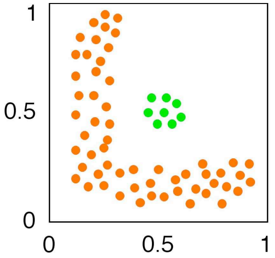

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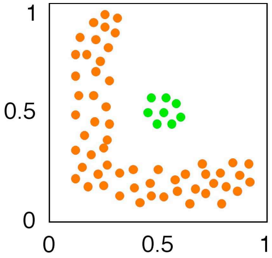

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Final test: random partitioning is not as good as `kmeans` in the local clustering phase.

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data set	#1	#2	#3	#4	#5
optimal k	8	8	6	6	2

Over-sampling

To over-sample they simply replicate. Now if rarity is:

- relative – then this is OK.
- absolute – then it is NOT!

Concluding Remarks

COG is a useful combination of:

- local clustering (unsupervised); and
- linear classification (supervised).

It generally improves performance.

Yet questions remain...