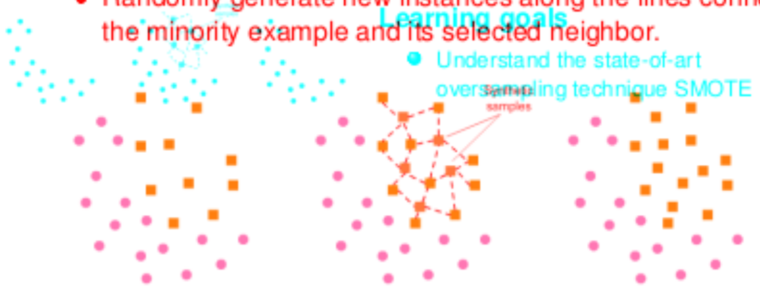
OVERSAMPLING: SMOTE

- SMOTE creates **synthetic instances** of minority class.
- Interpolate between neighboring minority instances.
- Instances are created in $\mathcal{X}$ rather than in $\mathcal{X} \times \mathcal{Y}$.
- Algorithm: For each minority class instance:
  - Find its k nearest minority neighbors.
  - Randomly select one of these neighbors.
  - Randomly generate new instances along the lines connecting the minority example and its selected neighbor.



Advanced Machine Learning

Imbalanced Learning: Sampling Methods Part 2

Learning goals

- Understand the state-of-art oversampling technique SMOTE

SMOTE: GENERATING NEW EXAMPLES

- Let $\mathbf{x}^{(i)}$ be the feature of the minority instance and let $\mathbf{x}^{(j)}$ be its nearest neighbor. The line connecting the two instances is

$$(1-\lambda)\mathbf{x}^{(i)} + \lambda\mathbf{x}^{(j)} = \mathbf{x}^{(i)} + \lambda(\mathbf{x}^{(j)} - \mathbf{x}^{(i)})$$

where $\lambda \in [0, 1]$.

- By sampling a $\lambda \in [0, 1]$, say $\tilde{\lambda}$, we create a new instance

$$\tilde{\mathbf{x}}^{(i)} = \mathbf{x}^{(i)} + \tilde{\lambda}(\mathbf{x}^{(j)} - \mathbf{x}^{(i)})$$

Example: Let $\mathbf{x}^{(i)} = (1, 2)^T$ and $\mathbf{x}^{(j)} = (3, 1)^T$. Assume $\tilde{\lambda} \approx 0.25$.

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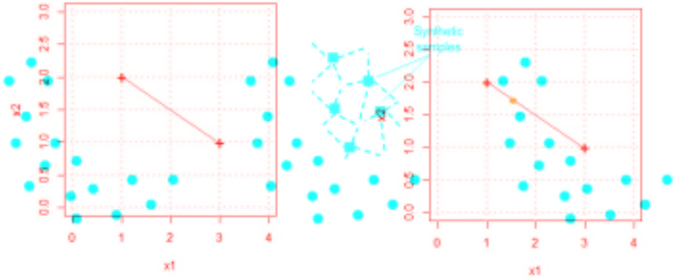

SMOTE: VISUALIZATION

For an imbalanced data situation, take four instances of the minority class. Let $K = 2$ be the number of nearest neighbors.

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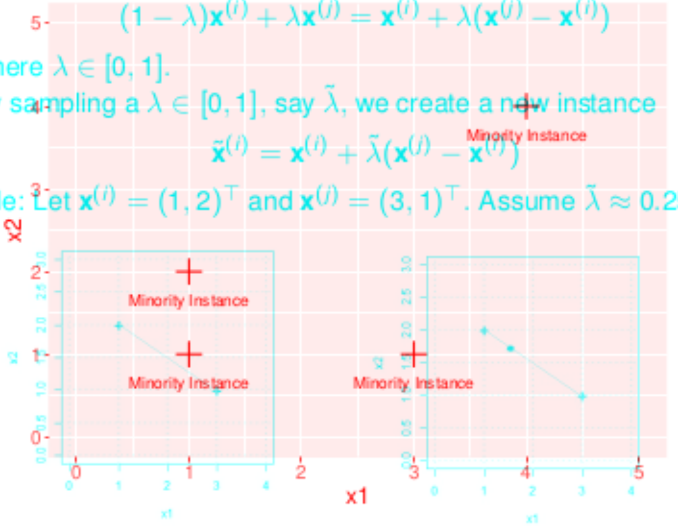

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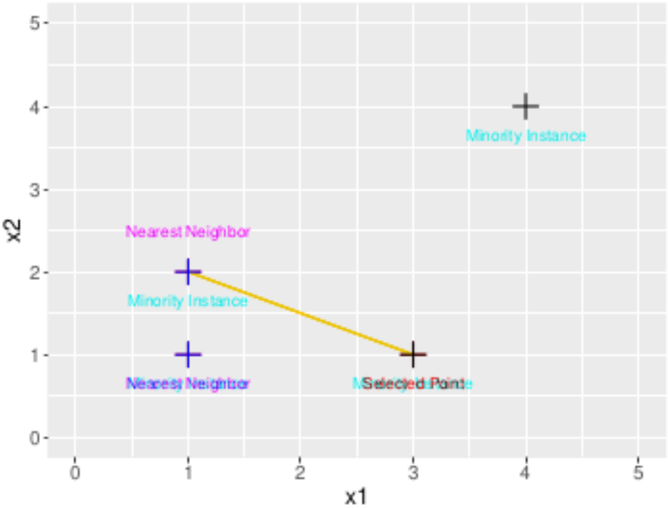

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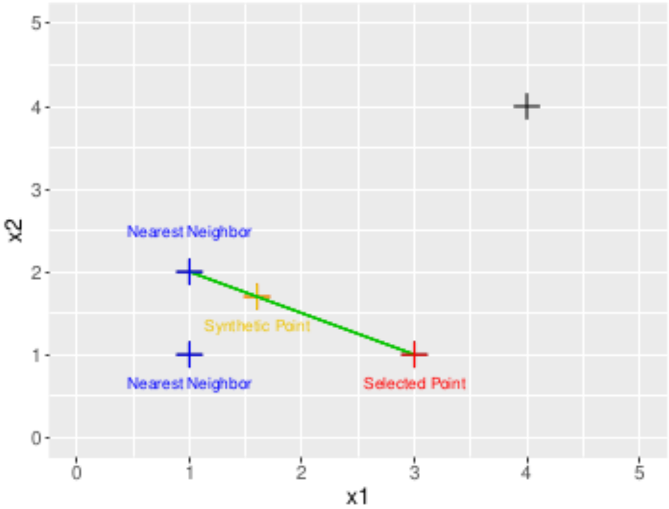

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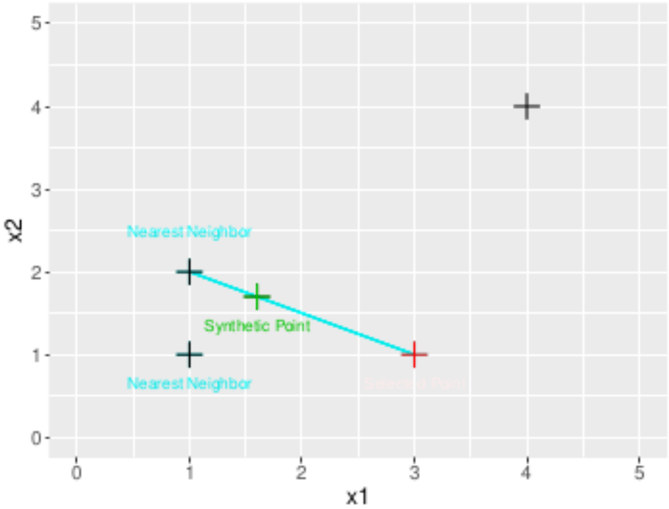

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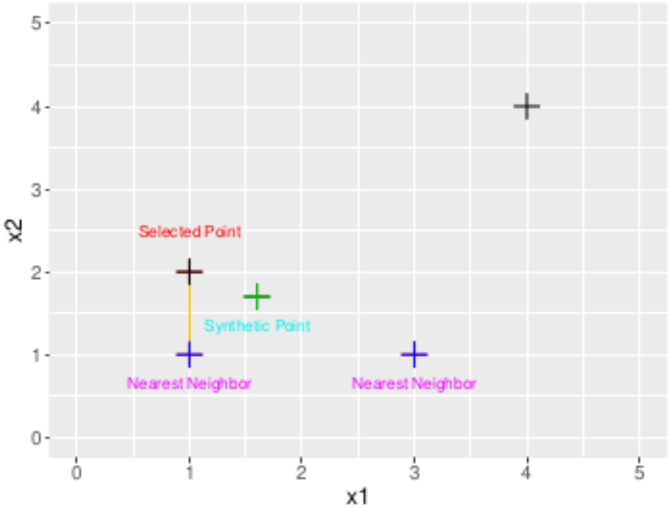

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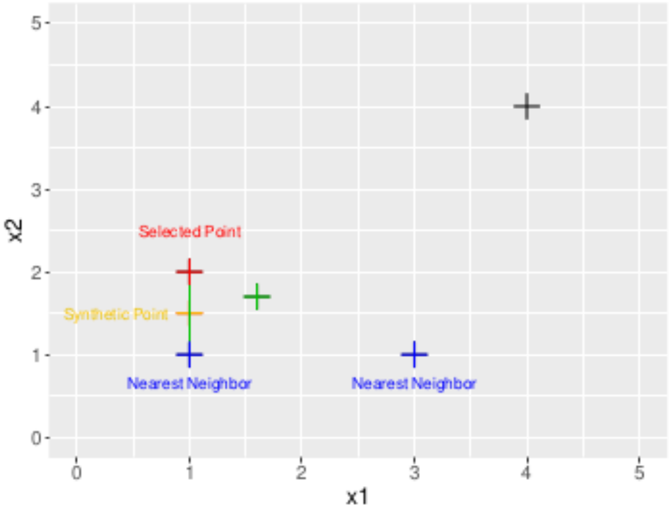

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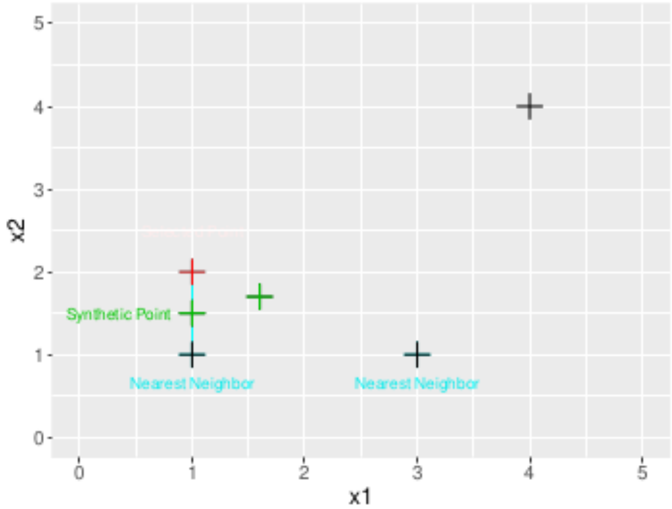

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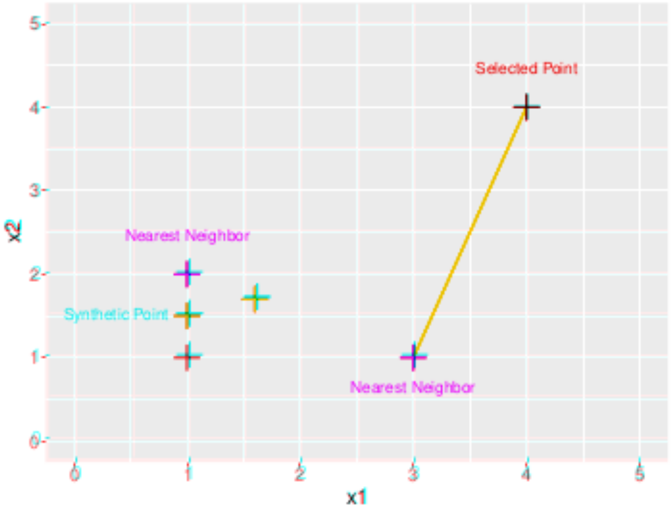

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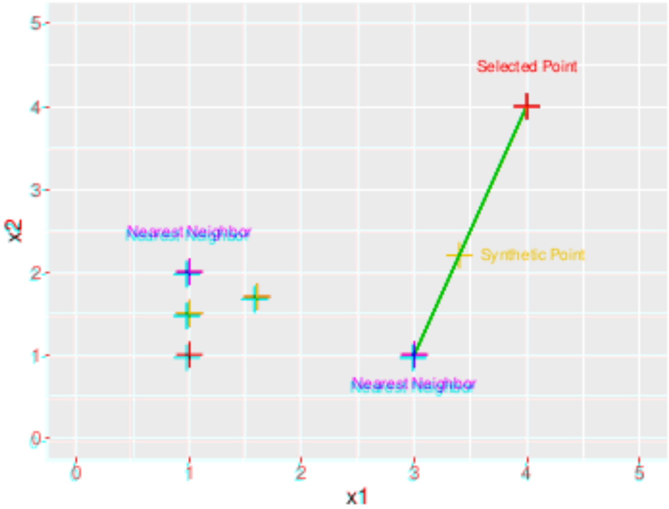

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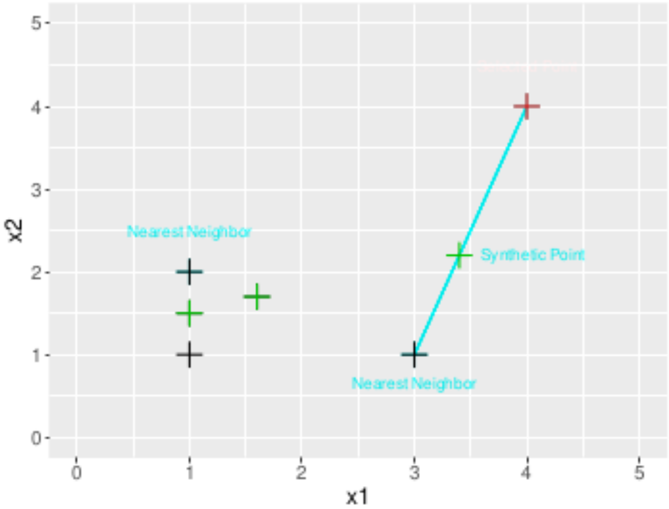
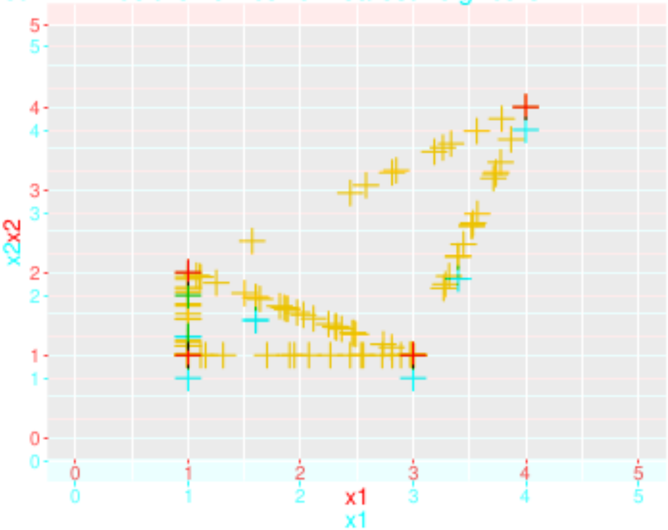


SMOTE: VISUALIZATION CONTINUED

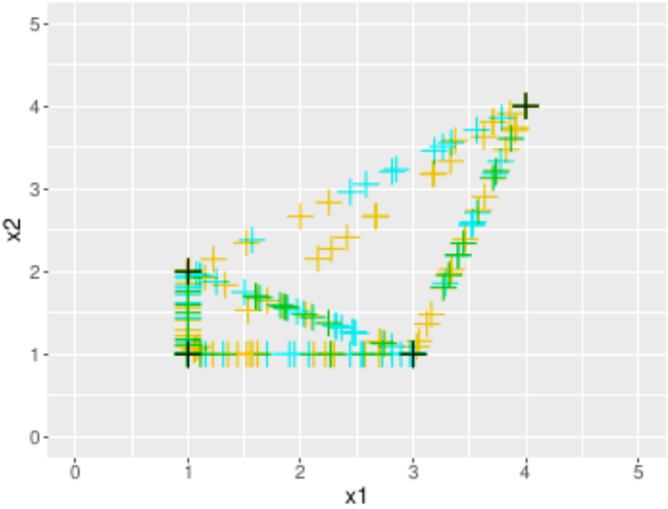
After 100 iterations of SMOTE for $K = 2$ we get:

class. Let $K = 2$ be the number of nearest neighbors.



SMOTE: VISUALIZATION CONTINUED

- After 100 iterations of SMOTE for $K = 3$ we get:

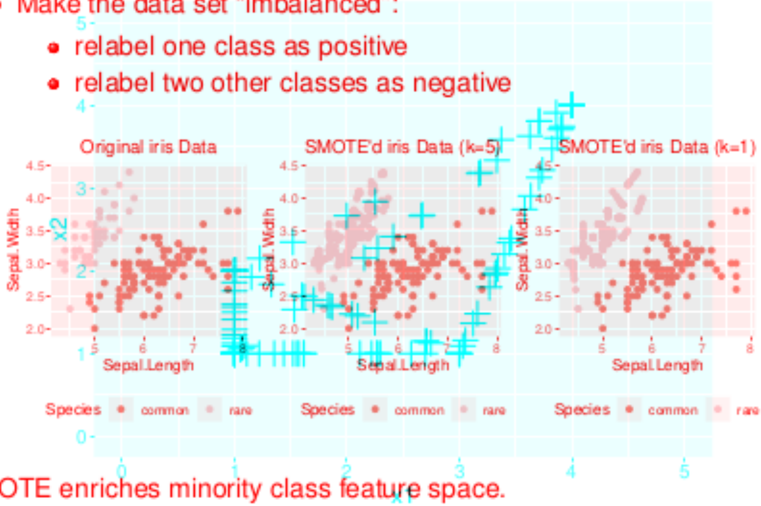


SMOTE: EXAMPLE

SMOTE: VISUALIZATION CONTINUED

After 100 iterations of SMOTE for $K = 3$ we get:

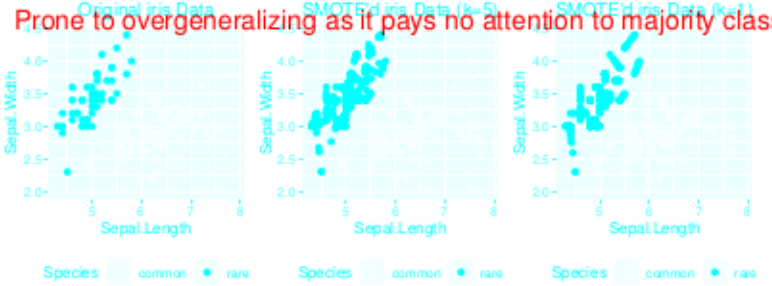
- Iris data set with 3 classes and 50 instances per class.
- Make the data set "imbalanced":
  - relabel one class as positive
  - relabel two other classes as negative



SMOTE enriches minority class feature space.

SMOTE: DIS-/ADVANTAGES

- Generalize decision region for minority class instead of making it quite specific, such as by random oversampling.
- Well-performed among the oversampling techniques and is the basis for many oversampling methods: Borderline-SMOTE, LN-SMOTE, . . . (over 90 extensions!)
- Prone to overgeneralizing as it pays no attention to majority class.



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COMPARISON OF SAMPLING TECHNIQUES

- Compare different sampling techniques on a binarized version of Optdigits dataset for optical recognition of handwritten digits.
- Use random forest with 100 trees, 5-fold cv, and F_1-Score.

Sampling technique	Class ratio	F1-Score
None	0.11	0.9239
Undersampling	0.68	0.9538
Oversampling	0.69	0.9538
SMOTE	0.79	0.9576

- Class ratios could be tuned (here done manually).
- Sampling techniques outperform base learner.
- SMOTE leads sampling techniques, although by a small margin.

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