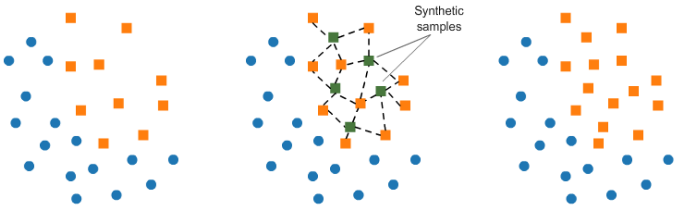
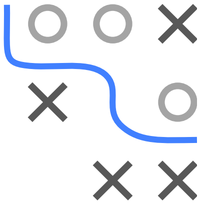
# OVERSAMPLING: SMOTE

- 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.

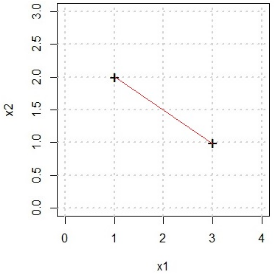


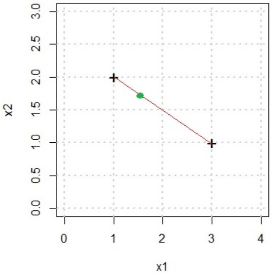
# SMOTE: GENERATING NEW EXAMPLES



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

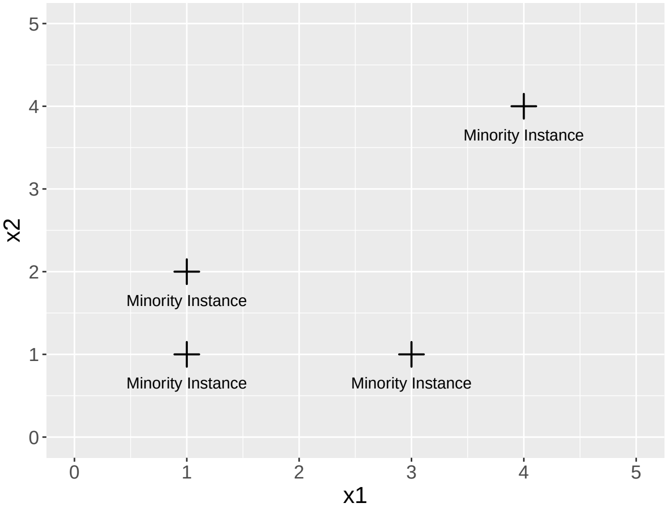
Example: Let $\mathbf{x}^{(i)} = (1, 2)^\top$ and $\mathbf{x}^{(j)} = (3, 1)^\top$. Assume $\tilde{\lambda} \approx 0.25$.

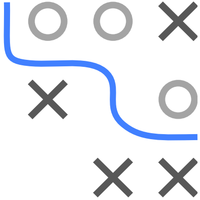


# SMOTE: VISUALIZATION

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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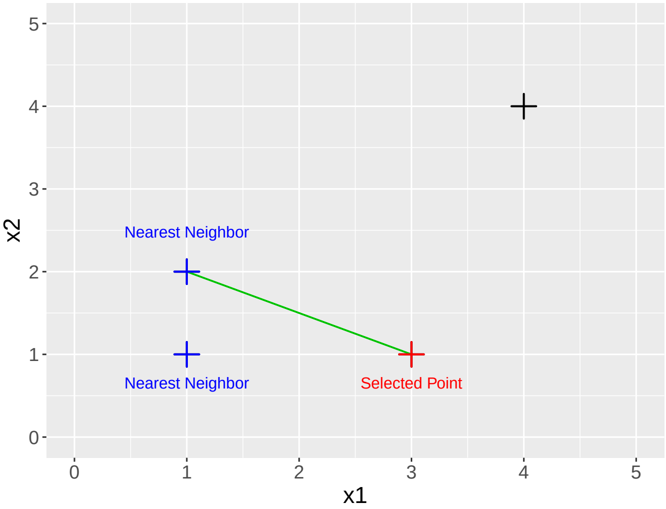


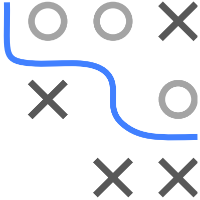

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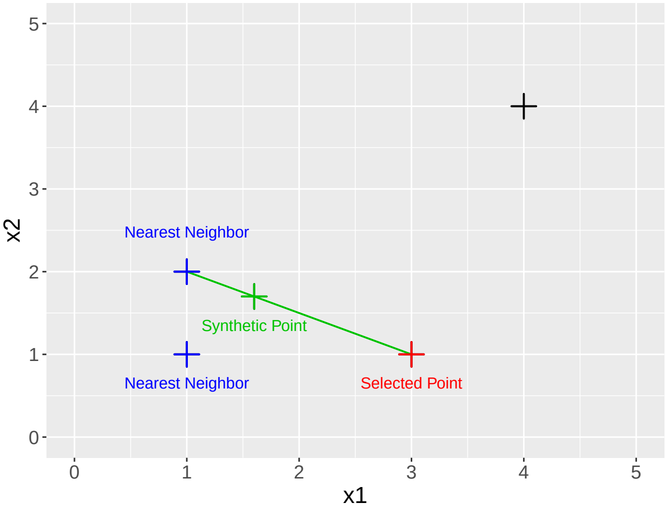


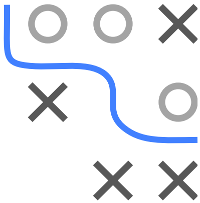

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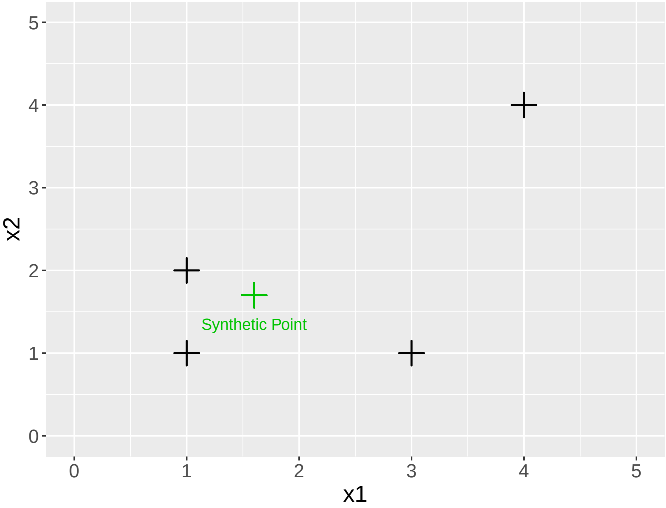

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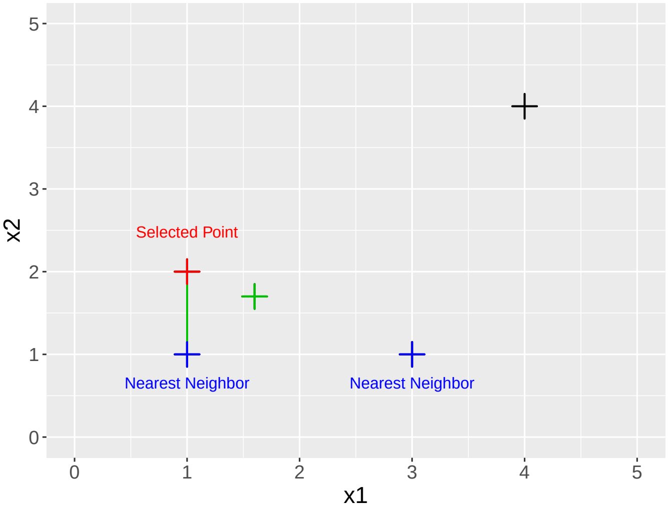

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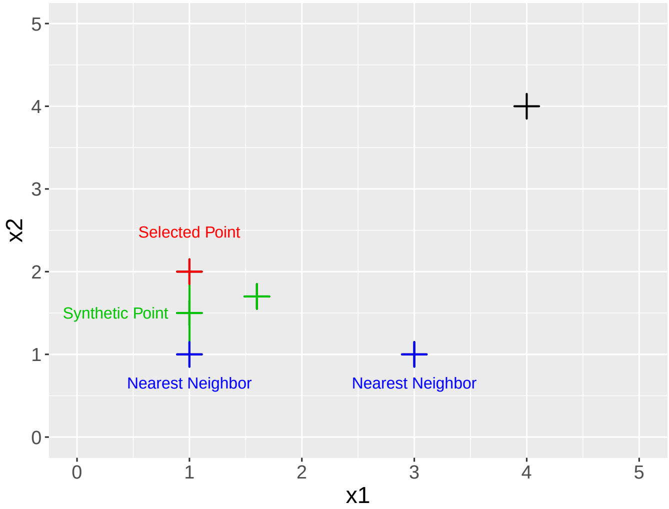


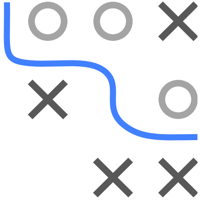

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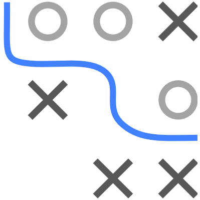

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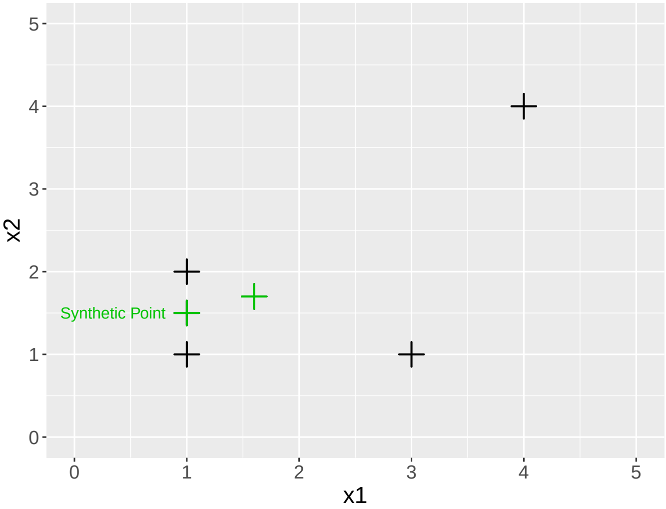

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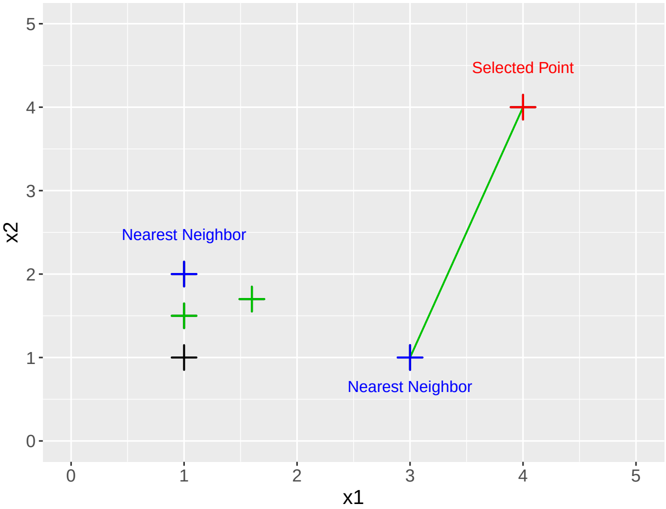


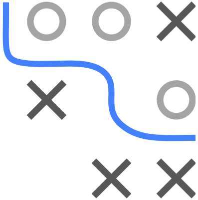

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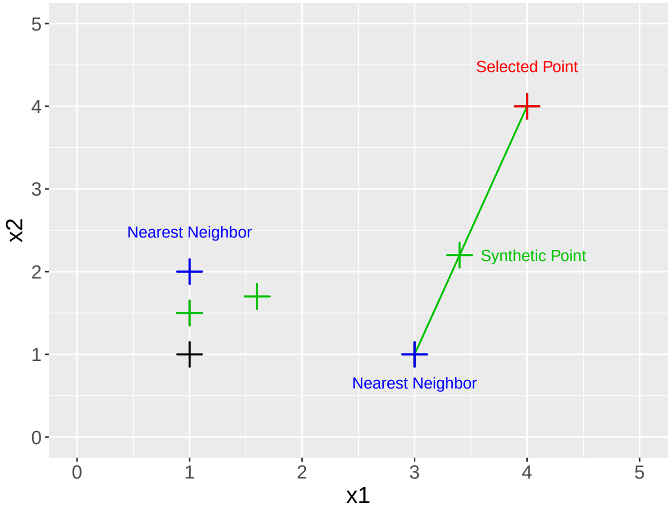


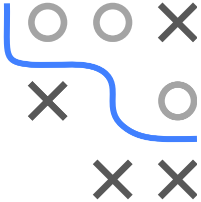

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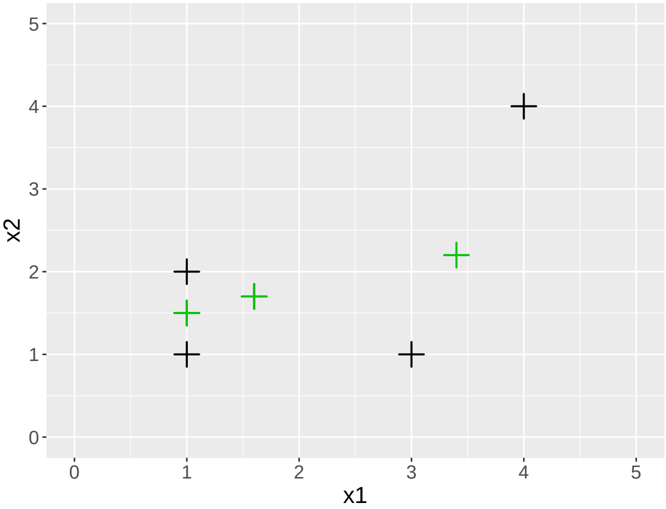
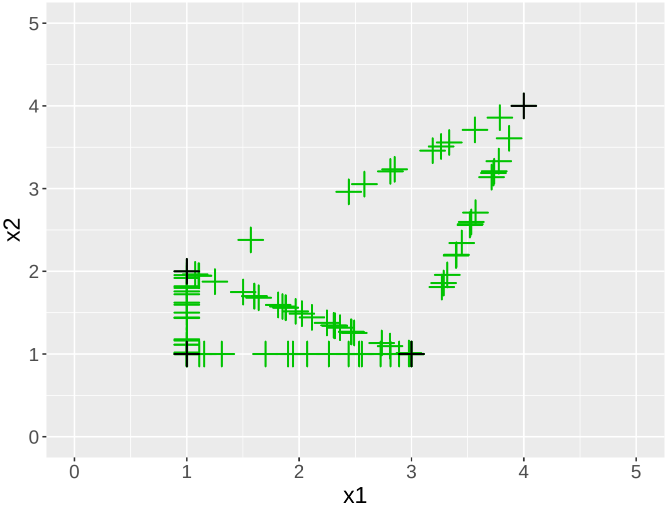
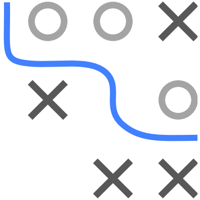


# SMOTE: VISUALIZATION CONTINUED

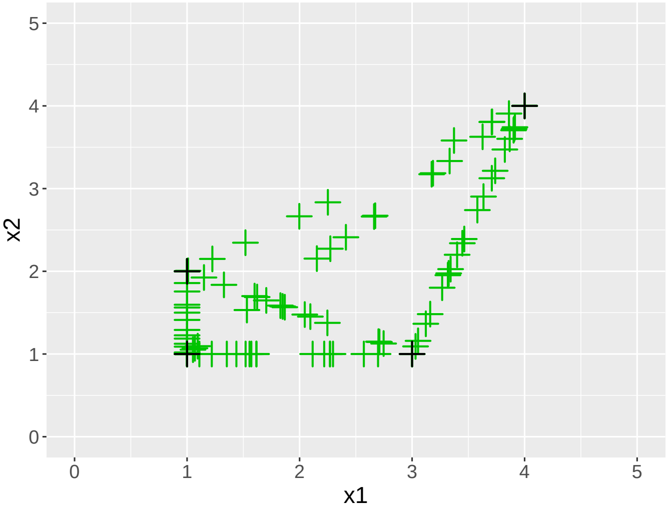
After 100 iterations of SMOTE for $K = 2$ we get:



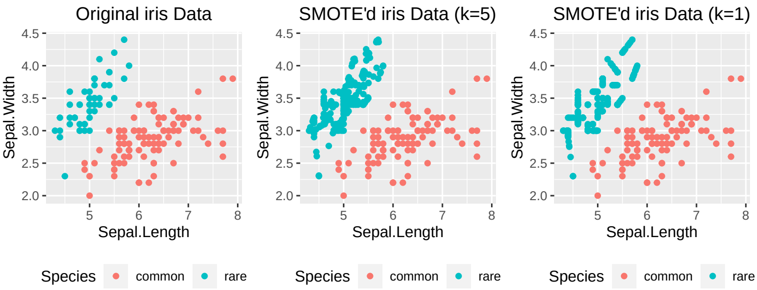
# SMOTE: VISUALIZATION CONTINUED

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



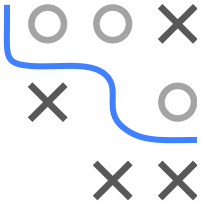
# SMOTE: EXAMPLE

- 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.

# 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.