CS685: Data Mining
Lazy Learners and Class Imbalance

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- Examples
    - K-nearest-neighbor (kNN) classifier
    - Case-based reasoning (CBR) classifier

K-Nearest-Neighbor (KNN) Classifier

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- Finding k nearest neighbors is costly without any pre-processing or indexing

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- Can be considered as a special case of KNN classifier

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- Over-sampling the less frequent class
  - Ends up choosing a point multiple times
  - May not help or may overfit

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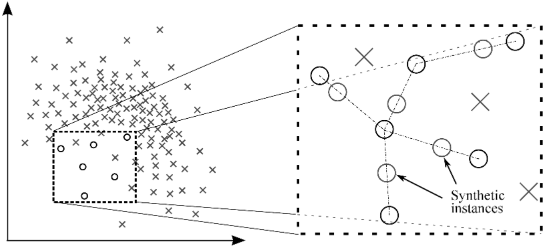
- For a randomly selected point $\vec{u}$, find a random nearest neighbor $\vec{w}$ within the *same* class
- Generate a new point $\vec{v}$ as

$$\vec{v} = \vec{u} + p \cdot (\vec{w} - \vec{u})$$

where $p \in (0, 1)$ is a uniform random number



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- Need a special strategy if none of the classes is assigned
- For m original classes, $2^m - 1$ combinations of classes
- Requires large training set