Let's do some KNNs

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Project Goal

KNNs

- 1. Take a test instance
- 2. Sort all train instances by distance to it
- 3. Take the K closest ones
- 4. Majority vote for class
- 5. Predict!

KNNs - the special sauce

- 1. Take a test instance
- 2. Sort all train instances by distance to it
- 3. Take the K closest ones
- 4. Majority vote for class 🥆
- 5. Predict!

We can do something else here!

Specifics, Techniques

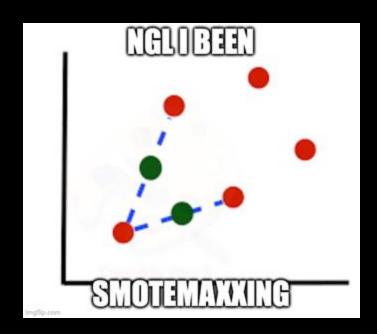
Our Versions:

- 1. Regular KNN (majority vote)
- 2. Weighted Averaging (vote but weighted by 1/frequency of class)
- 3. Weighted Distancing (weighted 1/distance)
- 4. Local Density Averaging
 - Ok, this one's a little complex:
 - For each neighbor:
 - Look at all other train points within radius R
 - Count em up, get local density
 - Normalize local density between all the neighbors
 - Weight by this normalized value
- All of em combined



Preprocessing?

- SMOTE



What is SMOTE?

- Synthetic Minority Oversampling TEchnique
- Basically, take minority class, choose a point, grab the K-nearest neighbors, and place a new synthetic point somewhere randomly on the line in between the neighbor and the point. Repeat until all classes have the same number of instances.



So, our categories:

- Regular KNN
- Weighted Averaging KNN
- Weighted Distancing KNN
- Local Density Averaging KNN
- All Methods Combined KNN
- Regular KNN with SMOTE
- Weighted Averaging KNN with SMOTE
- Weighted Distancing KNN with SMOTE
- Local Density Averaging KNN with SMOTE
- All Methods Combined KNN with SMOTE



How did we find the optimal K and R values?

- Original plan was to search through them by trying a bunch
- Problem: code takes a really long time to run
- Solution: try a few, and hope we found the best one! (we're pretty confident)

We selected K = 5, R = 30

The Dataset

Goals for Dataset

- Skewed class distribution
- Noise (bad data that slipped through preprocessing)
- Regular KNN can't get above 75% accuracy



Synthetically-Generated Dataset

- 10 attributes
- 3 classes:
 - Majority class of 1105 instances, centered at (0,0...0) with a standard deviation of 3
 - Minority class of 409 instances, centered at (3,3...3) with a standard deviation of 7
 - Minority class of 386 instances, centered at (-3,-3...-3) with a standard deviation of 7

Started with blobs of 1000, 300, 300 instances, then added 300 instances of random noise (105 to majority class, 109 to first minority, 86 to second minority)

Train-Test Split, SMOTE

80% to train set, 20% to test set

1520 train instances 380 test instances

2652 train instances after SMOTE

The Results

Non-SMOTE	SMOTE
73.42%	77.11%
76.58%	77.11%
73.68%	77.63%
74.47%	77.37%
75.26%	76.58%
	73.42% 76.58% 73.68%

How about the minorities?

- Not great, but improved



(% accuracy)	Class 1	Class 2
Regular KNN	38.96%	56.10%
Weighted Averaging	53.25%	58.54%
Regular KNN (with SMOTE)	54.55%	64.63%
Weighted Distancing (SMOTE)	55.84%	64.63%

(16.88% increase!) (8.53% increase!)

Results, Explained

- Surprisingly, all the methods increased the accuracy!
- SMOTE is really good!
- After using SMOTE, the other methods aren't as useful as there's no class imbalance
 - (for example, weighted averaging now does nothing at all)
- However, weighted distancing is still effective

Why is the accuracy still not 100%?

- These techniques aren't perfect
- But...
 - There is random noise in the data
 - The clusters overlap so it's impossible to tell some apart
- Given this, the improvement from ~73% to ~78% is pretty good!



Conclusion

To Conclude:

- KNNs do struggle with skewed and noisy data
- Different weighting methods can help
- SMOTE is very cool
- If you combine all the methods, it doesn't actually improve



Looking back...

- Probably put too much noise in the dataset

- Minority classes were 30%+ noise, so they really can't get above 70%

accuracy



Looking forward...

- With more computing resources:
 - More exhaustive search of K and R values
 - Multiple datasets
 - More advanced weighting/preprocessing methods





Any questions?