Data Science

Introduction to Machine Learning:
Random Forests, k-NN, Feature Engineering

July 9, 2021

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A quick survey of other ML methods

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   1.1 Linear Regressions
   1.2 Decision Trees
2. What else is out there?

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3. Is there any other way, specific to decision trees?
4. Yes, Just make more trees!

Random forests

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3. Solution (part 2): You don't use *all* of the features in the DTs

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2. Solution (part 1): You don't use the whole dataset to train all of them.
3. Solution (part 2): You don't use *all* of the features in the DTs
4. These parts are known as *baggin* and *random feature selection*

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   4.1 It depends on whether you need a classifier!

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2. $\frac{1}{|B|} \sum_{j \in B} y_j$

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1. For a classifier, just treat it as a vote!

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2. This reduces the correlation *between* trees!

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Random Trees (classifier) with SKLearn:

```
from sklearn.ensemble import RandomForestClassifier

classifier = RandomForestClassifier(n_estimators=N)
classifier = classifier.fit(X, Y)
```

Random Trees (regressor) with SKLearn:

```
from sklearn.ensemble import RandomForestRegressor

classifier = RandomForestRegressor(n_estimators=N)
classifier = classifier.fit(X, Y)
```

Other useful parameters:

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2. `max_samples`: How many samples you'll allow for each T
3. `min_samples_leaf`: How many samples needed for a leaf node to be created.

The company you keep

What if we don't want to think too hard about what our features mean?[2]

[2]This is a caricature!

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1. The human brain is very good at pattern matching (this is good and bad)
2. One way we determine what 'group' something belongs to is to see what it's near!
3. Let's write a program to do that.

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k-NN

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4. This can give us an *ordering* of the nearest neighbors.

$k\ldots$

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2. When $k = 2$, we only care about the two closet points, and they ‘vote’.
3. When $k = 3$, we only care about the... you get it.

Discussion time.

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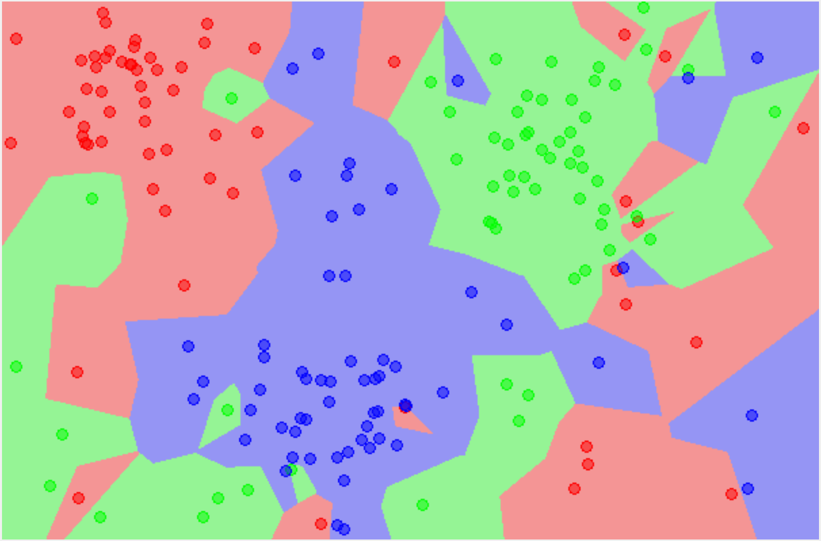
1. We only have to store the dataset in a way that let's us calculate the nearest neighbor(s)

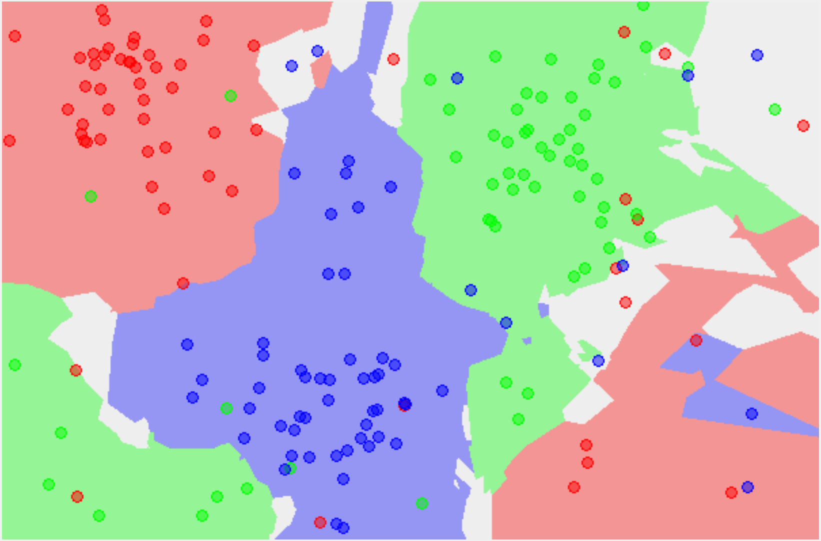
Discussion time 2.

What do we think k-NN might be good for?

Let's take a look (1NN):



Let's take a look (5NN):



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1. `sklearn.neighbors.KNeighborsClassifier`
2. Defaults to $k = 5$
3. You can also play with the `metric` and `p` parameters to change how distance is calculated (default is Euclidean distance).

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2. But sometimes we also want to add *interactions* between our terms.
3. To the notebook!

Thanks for your time!

:)