

- (a) (a) We're using a Naïve Bayes classifier. So the approach we're using is a smoothed probabilistic generative multiclass classifier.

The features I would use are whether each pixel is black or white. Given that the majority of all pixels will be black, I will model the presence of black pixels. The features are the colour of each of the individual pixels: so there are $150 \times 200 = 30000$ features. With this many features and any reasonably-sized training dataset, we will have a very high uncertainty on the probabilities of each feature given a class and each feature will be very uninformative.

The probability of an image i being in a class c

$$\log P(c|i) = \log P(c) + \sum_{w_i \in i} \lg P(w_i|c)$$

Note that we are using log-probabilities for numerical stability (else all probabilities would tend to zero with an unusably high uncertainty rapidly).

Unfortunately, the probabilities are not independent – so the Naïve Bayes assumption is broken since the probability of one pixel being black massively increases the probability of one of its neighbours being black.

- (b) The training data is the set of pixels from each of the hand-drawn images. It was collected by human annotators who annotated each picture according to what it represented.

The models parameters were estimated according to the following formula:

$$P(c) = \frac{\text{Count}(c)}{\sum_{c_i \in C} \text{Count}(c_i)}$$
$$P(w_i|c) = \frac{\text{Count}(w_i, c) + 1}{\text{Count}_{w_i \in V}(w_i) + |V|}$$

Where i is the image, C is the set of classes (house, tent, boat and igloo) and V is the set of all pixels.

- (b) We should granulate the images – reducing the resolution by merging several adjacent pixels into one pixel (this pixel being black if 3 or more constituent pixels are black). This will greatly reduce the uncertainty on the data. Currently the probability of any individual pixel being black is so low that it's got a very high uncertainty and fairly uninformative. If we were to merge 4 adjacent pixels and turn the images into a 75×100 pixel images (now only having 7500 features rather than 300000 we would be able to get much better predictions). Further improvements could involve a higher degree of merging however we would need to experimentally test to find out the optimal degree of merging and what the feature should be (ie I suggest the resultant pixel should be black if 3 or more of the subpixels are black – but maybe 4 or more or 2 or more would be more appropriate).

This should improve results since it massively decreases the uncertainty on probabilities.

- (c) (a) Door or no Door, Sea or no Sea, lots of Curved lines or few Curved lines (what constitutes lots of curved lines would require testing), Roof or no Roof.

Igloos and tent's don't have doors, only boats and houses can have the sea (although houses are far less likely to have the sea, while tents can not have the sea at all), houses and tents are less likely than igloos or boats to have curved lines while boats and igloos are likely to have more curved lines and only houses and boats will have rooves.

I think these features would be discriminative and would be possible to predict automatically.

These features would allow us to discriminate between the classes fairly well.

- Door or no Door

Houses and boats have doors so this feature would be discriminative. This would also be relatively easy to predict automatically since doors have a fairly uniform shape (square with a circle inside it).

- Sea or no Sea

Almost all drawings of boats would have the sea while very few of any other category would have the sea. This feature would be very good at discriminating boats and very prevalent while still being moderately easy to predict automatically.

- Lots of curved lines or few curved lines.

Igloos have a very high proportion of curved lines while the other classes have significantly fewer curved lines. This feature would be very discriminative for igloos – although it would require testing to find out an appropriate boundary for this. This would also be a prevalent feature.

- Roof or no roof

Houses and boats have roofs while the other classes don't usually. This would be discriminative and easy to make automatically due to the amount of shading on roofs.

- (b) We could incorporate the features described above as features in our pixel classifier. Our classifier would now have 7504 features – four of which are high level.

The high level features would have a very low uncertainty compared to the pixels – for example tents cannot be on the sea so anything on the sea would not be a tent. Our Naïve Bayes classifier is (should be) smoothed and so would move probability mass from higher probability features to this impossible feature. We could solve this by decreasing the smoothing for the high level features to account for this (so they'd still be smoothed but significantly less so – for example add-one smoothing for the pixel values and add-0.001 smoothing for the high-level features).