Learning from Data: Density Estimation - Likelihood

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Semester 1

http://www.inf.ed.ac.uk/teaching/courses/lfd

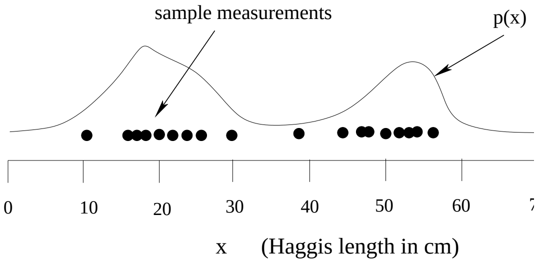
Density and Distribution Estimation

- The business of learning the distribution of data points.
- The catch-all of learning from data.
- In theory, every LFD problem is an issue of density estimation.
- In practice good general density estimation is hard.
- A generative approach. Answers the question ”How was the data generated?”

Recap on Probabilities

- Probabilities of all events sum to one.
- Probability density: probability per unit length. Probability integrates to one.
- Sample from a distribution: pick one value with a chance proportional to the probability (density). In the long run the number of each value will be proportional to the probability.

Examples

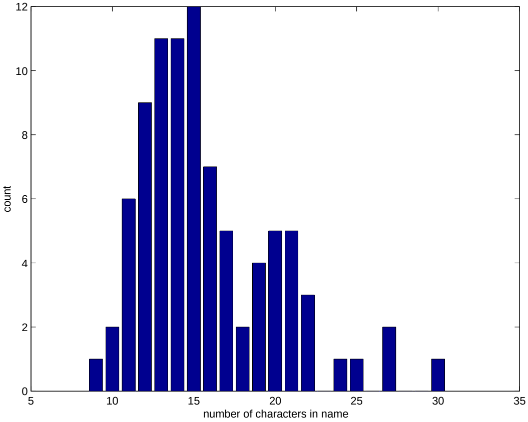


- Example from sheet. Length of Haggis. Evidence of a bimodal distribution.
- Continuous variables: probability *density*. Integrates to 1.

Example: Discrete Distributions

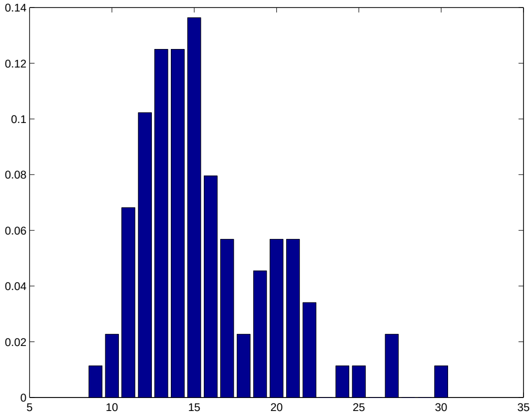
- Have data for the number of characters in names of people submitting tutorial requests:
  `9 10 10 11 11 11 11 11 11 12 12 12 12 12 12`
  `12 12 12 13 13 13 13 13 13 13 13 13 13 13`
  `14 14 14 14 14 14 14 14 14 14 14 15 15 15`
  `15 15 15 15 15 15 15 15 15 16 16 16 16 16`
  `16 16 17 17 17 17 17 18 18 19 19 19 19 20`
  `20 20 20 20 21 21 21 21 21 22 22 22 24 25`
  `27 27 30`
- Discrete data.
- Can build a frequency table of the data.

Frequency

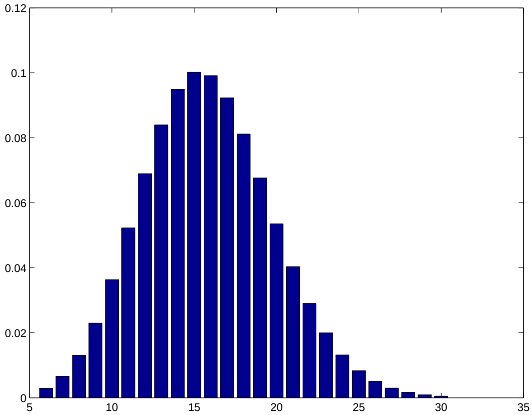


12
10
8
6
4
2
0
count
5
10
15
20
25
30
35
number of characters in name

Normalised frequency

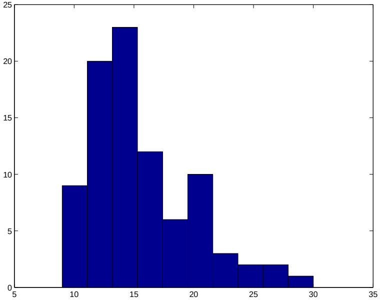


Possible Estimated Distribution?



Histograms

- Histograms are like frequency tables for continuous variables.
- Counts how many points between *a* and *b*. Plot $area = count$.

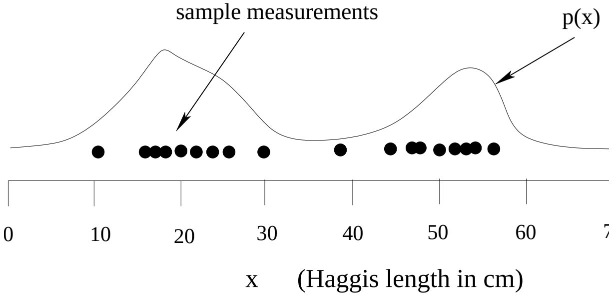


Framework

- Have some underlying probability distribution or density.
- This distribution is used to generate data.
- Each data point is generated independently from the same distribution.
- This is the *generative* model. It is the approach we could use to generate artificial data.

Example

Haggis again!



Inverse Problem

- BUT what if we don't know the underlying distribution.
- Want to *learn* a good distribution that fits the data we do have.
- How is *goodness* measured?
- Given some distribution, we can ask how likely it is to have generated the data.
- In other words what is the probability (density) of this particular data set given the distribution.
- A particular distribution explains the data better if the data is more probable under that distribution.

Likelihood

- $P(D|M)$. The probability of the data D given a distribution (or model) M. This is called the likelihood of the model.
- This is

$$P(D|M) = \prod_{i=1}^{N} P(\mathbf{x}_i|M)$$

  i.e. the product of the probabilities of generating each data point individually.
- This is a result of the independence assumption.
- Try different M (different distributions). Pick the M with the highest likelihood $\rightarrow$ Maximum Likelihood Approach.

Boolean distribution

- Data 1 0 0 1 0 1 0 1 0 0 0 0 0 1 0 1 1 1 0 1.
- Three hypotheses:
  - $M = 1$ - Generated from a fair coin. 1=H, 0=T
  - $M = 2$ - Generated from a die throw 1=1, 0 = 2,3,4,5,6
  - $M = 3$ - Generated from a double headed coin 1=H, 0=T
- Likelihood of data. Let c=number of ones:

$$\prod P(x_i|M) = P(1|M)^c P(0|M)^{20-c}$$

- $M = 1$: Likelihood is $0.5^{20} = 9.5 \times 10^{-7}$
- $M = 2$: Likelihood is $(1/6)^9\ (5/6)^{11} = 1.3 \times 10^{-8}$
- $M = 3$: Likelihood is $0^9\ 1^{11} = 0$

Boolean distribution

- Data 1 0 0 1 0 1 0 1 0 0 0 0 0 1 0 1 1 1 0 1.
- Continuous range of hypotheses: $M = k$ - Generated from a Boolean distribution with $P(1|M = k) = k$.
- Likelihood of data. Let c=number of ones:

$$\prod P(x_i|M = k) = k^c(1 - k)^{20-c}$$

- Maximum Likelihood hypothesis? Differentiate w.r.t. k to find maximum
- In fact usually easier to differentiate $\log P(D|M)$: log is monotonic.
- $d \log P(D|M)/dk = c/k - (20 - c)/(1 - k)$
- So $c(1 - k) - (20 - c)k = 0$. This gives $k = c/20$. Maximum likelihood is unsurprising.
- Warning: do we always believe all possible values of k are equally likely?

Summary

- Density and distribution estimation. Find the density from which the data was generated.
- Given a density, can generate artificial independently and identically distributed (IID) data.
- Likelihood. Maximum likelihood. Log likelihood.
- Given the data, and a model (a set of hypotheses - either discrete or continuous) we can find a maximum likelihood model for the data.
- Next lecture: the Gaussian distribution, multivariate densities.