

# Statistical Data Analysis

## Discussion notes – week 6

- Problem sheet 3
- Comments on scikit-learn
- Comments on p-values

## Problem sheet 3

**Exercise 1 [6 marks]:** Consider two continuous random variables  $x$  and  $y$  that follow the joint pdf  $f(x, y)$  and define  $u = x + y$ . Show that the pdf of  $u$  can be written

$$g(u) = \int_{-\infty}^{\infty} f(x, u - x) dx .$$

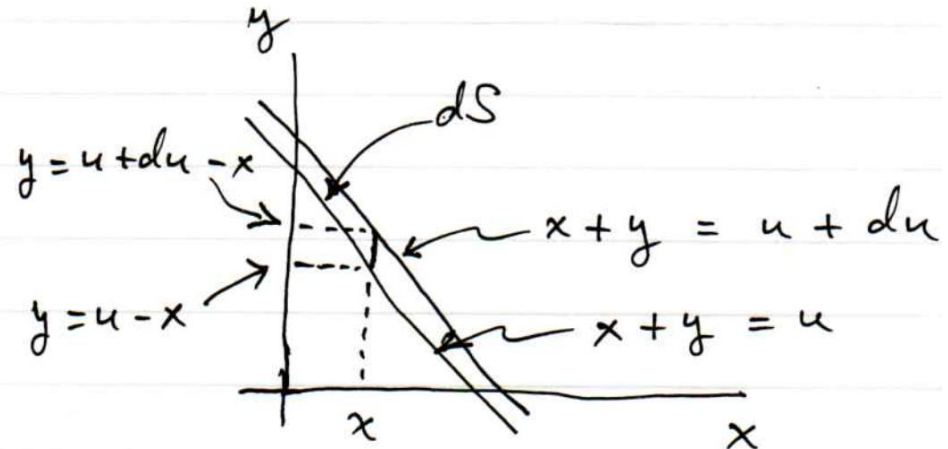
Use a method analogous to what was shown in the lectures for the product of two random variables (see p. 9 of the week 2 slides).

1)  $x, y \sim f(x, y)$

Define  $u = x + y$

From week 2 slides p. 9,

$$g(u) du = \int_{dS} f(x, y) dx dy$$



# 1 (cont.)

$$\Rightarrow g(u) du = \int_{-\infty}^{\infty} \underbrace{\int_{u-x}^{u+du-x} f(x,y) dy}_{f(x, u-x) \cdot \underbrace{du}_{\text{interval width}}} dx$$

approx. const. in infinitesimal interval

$$g(u) du = \int_{-\infty}^{\infty} f(x, u-x) dx du$$

Q.E.D.

( or can carry out integration in opposite order,

$$g(u) = \int_{-\infty}^{\infty} f(u-y, y) dy$$

**Exercise 2 [7 marks]:** Suppose  $x$  and  $y$  are independent and exponentially distributed each with mean values  $\theta$  and define  $u = x + y$ . By using the result from Ex. 1, find the pdf of  $u$ . (In fixing the limits of integration, remember that the pdf is nonzero only for  $x \geq 0$  and  $y \geq 0$ .)

$$x \sim \frac{1}{\xi} e^{-x/\xi}, \quad y \sim \frac{1}{\xi} e^{-y/\xi} \quad \text{indep}$$

$$\Rightarrow f(x, y) = \frac{1}{\xi^2} e^{-(x+y)/\xi}, \quad \text{since } x, y \text{ indep.}, \quad f(x, y) = f_x(x) f_y(y)$$

$$u = x + y$$

$$g(u) = \int_{-\infty}^{\infty} f(x, u-x) dx$$

↑  
nonzero for  $x > 0$

and  $y = u - x > 0$

$$\Rightarrow \underline{u > x}$$

$$\Rightarrow g(u) = \int_0^u \frac{1}{\xi^2} e^{-(x + u - x)/\xi} dx$$

$$= \frac{1}{\xi^2} e^{-u/\xi} \int_0^u dx$$

$$= \frac{u}{\xi^2} e^{-u/\xi} \quad u \geq 0.$$

3.

**Exercise 3 [7 marks]:** Consider a continuous random variable  $x$  that follows the pdf  $f(x)$  with cumulative distribution  $F(x)$ , and suppose  $r$  follows a uniform distribution on  $[0, 1]$ . Prove (as was claimed in the lectures) that if we set  $F(x) = r$  and solve for  $x$ , that  $x(r)$  follows the pdf  $f(x)$ . To do this, use the method discussed in the lectures for finding the pdf of a function, and use the inverse function theorem, which says that

$$\frac{d}{dr}F^{-1}(r) = \frac{1}{\frac{dF}{dx}(x(r))}.$$

3)  $x$  follows  $f(x)$

$$\text{cdf is } F(x) \Rightarrow f(x) = \frac{dF}{dx}$$

$$r \sim \text{Uniform}[0, 1]$$

$$\text{i.e. } g(r) = 1, \quad 0 \leq r \leq 1$$

$$\text{If } F(x) = r \Rightarrow x = F^{-1}(r)$$

pdf of  $x(r)$  is

$$p(x) = g(r) \left| \frac{dr}{dx} \right| = \frac{g(r)}{\left| \frac{dx}{dr} \right|}$$

$$\frac{dx}{dr} = \frac{d}{dr} F^{-1}(r) = \frac{1}{\frac{dF}{dx}(x(r))} = \frac{1}{f(x(r))}$$

$$\Rightarrow \frac{dr}{dx} = f(x)$$

$$\Rightarrow p(x) = \overset{g(r)}{1} \times \overset{\left| \frac{dr}{dx} \right|}{f(x)} = \underline{f(x)}$$

# Software for Machine Learning

We will practice ML with the Python package scikit-learn

`scikit-learn.org` ← software, docs, example code

scikit-learn built on NumPy, SciPy and matplotlib, so you need

```
import scipy as sp
import numpy as np
import matplotlib
import matplotlib.pyplot as plt
```

and then you import the needed classifier(s), e.g.,

```
from sklearn.neural_network import MLPClassifier
```

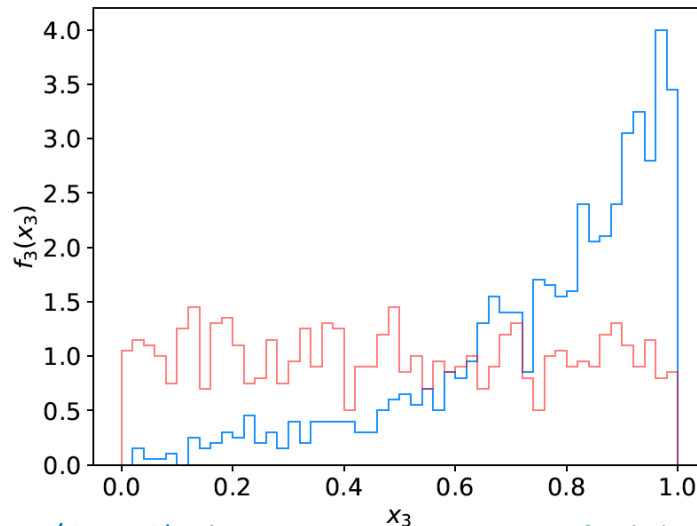
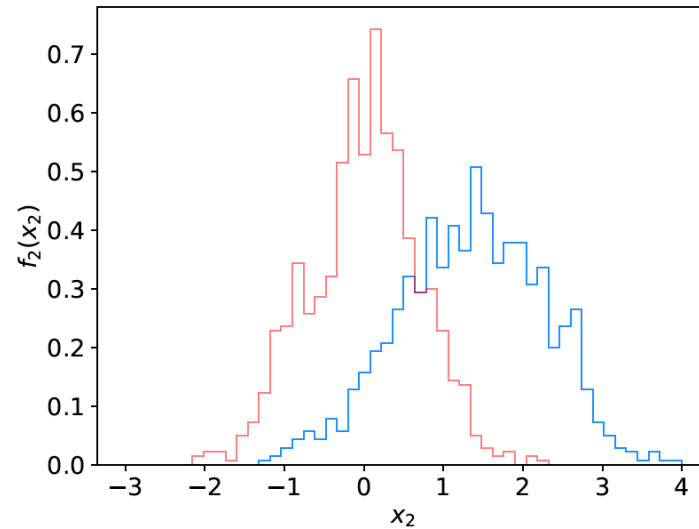
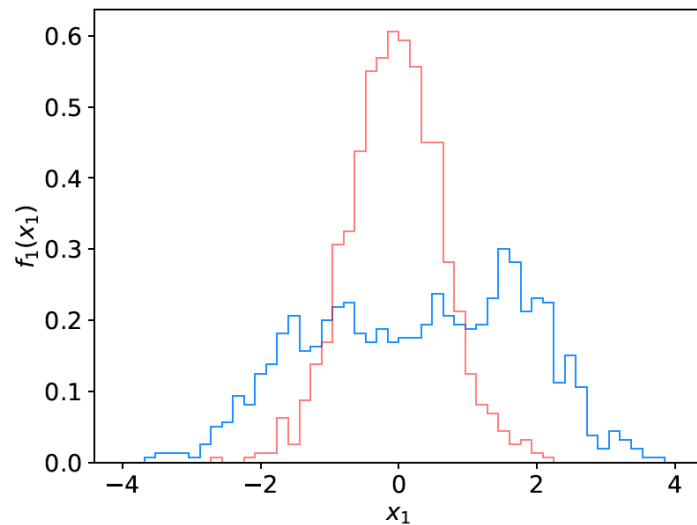
For a list of the various classifiers in scikit-learn see the docs on `scikit-learn.org`, also a very useful sample program:

```
http://scikit-learn.org/stable/auto_examples/classification/plot_classifier_comparison.html
```



# Example: the data

We will do an example with data corresponding to events of two types: signal ( $y = 1$ , blue) and background ( $y = 0$ , red).



Each event is characterised by 3 quantities:  $\mathbf{x} = (x_1, x_2, x_3)$ .

Components are correlated.

Suppose we have 1000 events each of signal and background.

# Reading in the data

scikit-learn wants the data in the form of numpy arrays:

```
# read the data in from files,  
# assign target values 1 for signal, 0 for background  
sigData = np.loadtxt('signal.txt')  
nSig = sigData.shape[0]  
sigTargets = np.ones(nSig)  
bkgData = np.loadtxt('background.txt')  
nBkg = bkgData.shape[0]  
bkgTargets = np.zeros(nBkg)  
  
# concatenate arrays into data X and targets y  
# split into two parts: use one for training, the other for testing  
X = np.concatenate((sigData,bkgData),0)  
y = np.concatenate((sigTargets, bkgTargets))  
  
# split data into training and testing samples  
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.5,  
                                                    random_state=1)
```

# Create, train, evaluate the classifier

Create an instance of the MLP (multilayer perceptron) class and “train”, i.e., adjust the values of the weights to minimise the loss function.

Here we request 3 hidden layers with 10 nodes each:

# create classifier object and train

```
clf = MLPClassifier(hidden_layer_sizes=(10,10,10), activation='tanh',  
                    max_iter=2000, random_state=6)  
clf.fit(X_train, y_train)
```

Use test data to see what fraction of events are correctly classified (default takes threshold of 0.5 for decision function)

# evaluate its accuracy (= 1 – error rate) using the test data

```
y_pred = clf.predict(X_test)  
print(metrics.accuracy_score(y_test, y_pred))
```

# Evaluating the decision function

So now for any point ( $x_1, x, x_3$ ) in the feature space, we can evaluate the decision:

# Test evaluation of decision function for a specific point in feature space

```
xt = np.array([0.37, 2.46, 0.42]).reshape((1,-1))
```

```
#t = clf.decision_function(xt)[0]          # not available for MLP
```

```
t = clf.predict_proba(xt)[0, 1]          # for MLP use this instead
```

Usually we have an array of points in  $x$ -space, so we can get an array of probabilities:

```
t = clf.predict_proba(X_test)[: , 1]      # returns prob to be of type  $y=1$ 
```

Can get this separately for the signal and background events and make histograms (see sample code).

Note for most other classifiers, the decision function is called `decision_function` – use this instead of `predict_proba`.

# On defining a $p$ -value

Earlier it was argued that the region of “equal or lesser compatibility” with  $H$  had greater compatibility with the predictions of some alternative hypothesis.

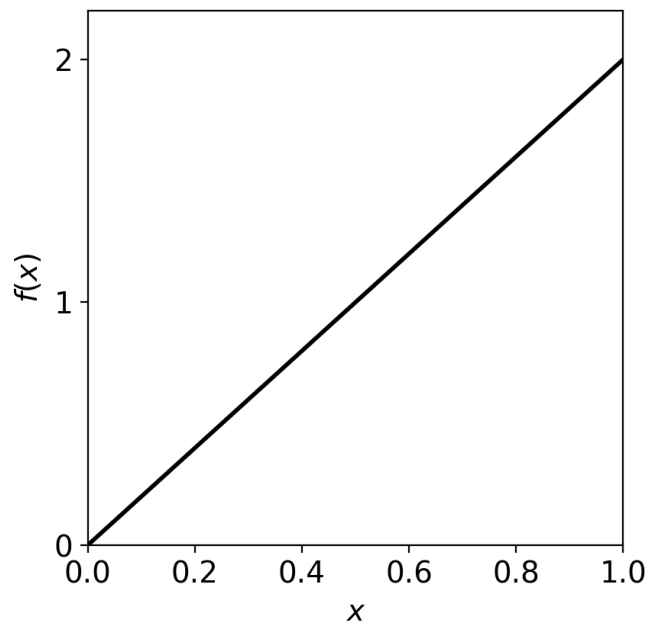
But shouldn't it be possible to identify such a region by using the pdf  $f(x|H)$ ?

In general, no.

Consider cubic crystal grains produced by a process  $H$  that have a size distribution

$$f(x|H) = 2x, \quad 0 < x \leq 1$$

Observe grain of uncertain origin,  
measure  $x$ ,  
find  $p$ -value of  $H$ .



If we observe a value  $x_{\text{obs}}$ , naively we could regard  $x \leq x_{\text{obs}}$  as constituting equal or less agreement with the predictions of  $f(x|H)$ .

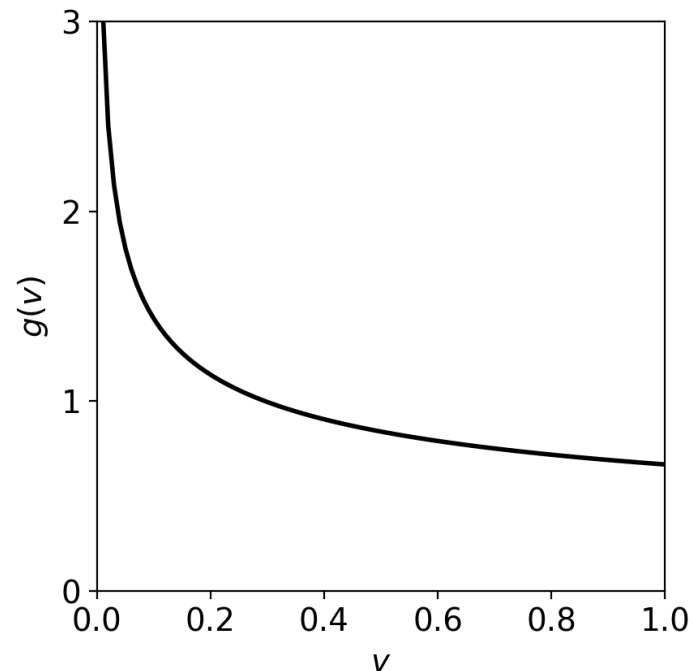
## On defining a $p$ -value (2)

But suppose we took the volume  $v = x^3$  of the cube to represent its size. The volume distribution is

$$g(v|H) = f(x(v)|H) \left| \frac{dx}{dv} \right|$$

$$= \frac{2}{3} v^{-1/3}$$

$$0 < v \leq 1$$



So now it appears that smaller sizes are more compatible with  $H$ .

Conclusion: deciding what region of data space constitutes greater or lesser compatibility with  $H$  cannot be done by looking at the data distribution alone; it requires that one consider an alternative  $H'$ .



# Psychology journal bans $P$ values

Test for reliability of results ‘too easy to pass’, say editors.

**Chris Woolston**

26 February 2015 | Clarified: [09 March 2015](#)

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A controversial statistical test has finally met its end, at least in one journal. Earlier this month, the editors of *Basic and Applied Social Psychology* (BASP) announced that the journal would no longer publish papers containing  $P$  values because the statistics were too often used to support lower-quality research<sup>1</sup>.

