T-61.3050 Machine Learning: Basic Principles Solution of Prerequisite Knowledge Test 2013

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1 Algebra, Probabilities:

a)

First, assume another function $g:\Omega\to\mathbb{R}$. Now as per the definition of the operator E, we write:

$$\begin{split} E[f(\omega) + g(\omega)] &= \sum_{\omega \in \Omega} P(\omega)(f(\omega) + g(\omega)) \\ &= \sum_{\omega \in \Omega} P(\omega)f(\omega) + P(\omega)g(\omega) \\ &= \sum_{\omega \in \Omega} P(\omega)f(\omega) + \sum_{\omega \in \Omega} P(\omega)g(\omega) \\ &= E[f(\omega)] + E[g(\omega)] \end{split}$$

Second, assume that t is a scalar, Now as per the definition of the operator E, we write:

$$\begin{split} E[tf(\omega)] & = & \sum_{\omega \in \Omega} P(\omega)(tf(\omega)) \\ & = & \sum_{\omega \in \Omega} tP(\omega)(f(\omega)) \\ & = & t \sum_{\omega \in \Omega} P(\omega)(f(\omega)) \\ & = & tE[f(\omega)] \end{split}$$

So, we can colclude that $E[\cdot]$ is a linear operator

b)

According to the definition of variance:

$$\begin{split} Var[f(\omega)] &= E[f(\omega) - E[f(\omega)])^2] \\ &= E[f(\omega)^2 - 2f(\omega)E[f(\omega)] + E[f(\omega)]^2] \\ &= E[f(\omega)^2] - E[2f(\omega)E[f(\omega)]] + E[E[f(\omega)]^2] \text{ //As } E[\cdot] \text{ is a linear operator} \\ &= E[f(\omega)^2] - 2E[f(\omega)]E[f(\omega)] + E[f(\omega)]^2E[1] \text{ //}E[f(\omega)] \text{ is scalar value} \\ &= E[f(\omega)^2] - E[2f(\omega)E[f(\omega)]] + E[f(\omega)]^2 \sum_{\omega \in \Omega} P(\omega) \\ &= E[f(\omega)^2] - 2E[f(\omega)]^2 + E[f(\omega)]^2 \text{ //It is given that } \sum_{\omega \in \Omega} P(\omega) = 1 \\ &= E[f(\omega)^2] - E[f(\omega)]^2 \end{split}$$

2 Matrix Calculus:

It is given that,

$$\mathbf{B} = \sum_{i=1}^{n} \lambda_i \mathbf{v}_i \mathbf{v}_i^T \tag{1}$$

Multiplying both side of (1) by \mathbf{v}_j where $j \in 1 \dots n$, we can write

$$\begin{aligned} \mathbf{B}\mathbf{v}_{j} &= \left(\sum_{i=1}^{n} \lambda_{i} \mathbf{v}_{i} \mathbf{v}_{i}^{T}\right) \mathbf{v}_{j} \\ \mathbf{B}\mathbf{v}_{j} &= \left(\lambda_{1} \mathbf{v}_{1} \mathbf{v}_{1}^{T} + \lambda_{2} \mathbf{v}_{2} \mathbf{v}_{2}^{T} + \ldots + \lambda_{n} \mathbf{v}_{n} \mathbf{v}_{n}^{T}\right) \mathbf{v}_{j} \\ \mathbf{B}\mathbf{v}_{j} &= \lambda_{1} \mathbf{v}_{1} \mathbf{v}_{1}^{T} \mathbf{v}_{j} + \lambda_{2} \mathbf{v}_{2} \mathbf{v}_{2}^{T} \mathbf{v}_{j} + \ldots + \lambda_{j} \mathbf{v}_{j} \mathbf{v}_{j}^{T} \mathbf{v}_{j} + \ldots + \lambda_{n} \mathbf{v}_{n} \mathbf{v}_{n}^{T} \mathbf{v}_{j} \\ \mathbf{B}\mathbf{v}_{j} &= \lambda_{j} \mathbf{v}_{j} \mathbf{v}_{j}^{T} \mathbf{v}_{j} // \operatorname{As} \mathbf{v}_{i}^{T} \mathbf{v}_{j} = \delta_{i,j} \text{ where } \delta_{i,j} = 1 \text{ when } i = j \text{ and } \delta_{i,j} = 0 \text{ when } i \neq j \text{ }) \\ \mathbf{B}\mathbf{v}_{j} &= \lambda_{j} \mathbf{v}_{j} \end{aligned}$$

So it is clear that λ_i and \mathbf{v}_i are Eigenvalues and Eigenvectors of the matrix \mathbf{B}

3 Algorithms:

The Algorithm:

GenFibonacciuptoN(n)Begin

- 1. Declare an Array Fib[1..n]
 - 2. Fib[1] = 1, Fib[2] = 1
 - 3. For each $i\in\mathbb{N}$ starting from 3 to n in ascending order, do
 - i) Fib[i] = Fib[i-2] + Fib[i-1]
 - 4. Return the array Fib[1..n]. The i-th index holds the i-th Fibonacci Number

End

Time Complexity:

- 1 Worst case time complexity is: T(n) = n 2 i.e. T(n) = O(n)
- $2\,$ The algorithm has linear time complexity with the growth of input size

4 Basic Data Analysis, Software Tools:

Matlab Code:

```
secondmax = 0;
maxi = 0;
secondmaxi = 0;
for i=1:16,
   for j=1:4000
       x(i) = x(i) + A(j,i);
       xsquare(i) = xsquare(i) + A(j,i)^2;
xvar(i) = xsquare(i)/4000 - (x(i)/4000)^2;
if xvar(i) > max
   secondmax = max;
   secondmaxi = maxi;
   max = xvar(i);
   maxi = i;
end
maxvariancecolumn = A(:,maxi);
secondmaxvariancecolumn = A(:,secondmaxi);
plot(secondmaxvariancecolumn, maxvariancecolumn, 'o');
```

Scatterplot of the the columns having largest variance:

