



中国科学院大学
University of Chinese Academy of Sciences

《课程名称》标题 子标题

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学生

背景介绍

Problem 1

Give an appropriate positive constant c such that $f(n) \leq c \cdot g(n)$ for all $n > 1$.

1. $f(n) = n^2 + n + 1, g(n) = 2n^3$
2. $f(n) = n\sqrt{n} + n^2, g(n) = n^2$
3. $f(n) = n^2 - n + 1, g(n) = n^2/2$

Solution

We solve each solution algebraically to determine a possible constant c .

Part One

$$\begin{aligned}
 n^2 + n + 1 &= \\
 &\leq n^2 + n^2 + n^2 \\
 &= 3n^2 \\
 &\leq c \cdot 2n^3
 \end{aligned}$$

Thus a valid c could be when $c = 2$.

Part Two

$$\begin{aligned}
 n^2 + n\sqrt{n} &= \\
 &= n^2 + n^{3/2} \\
 &\leq n^2 + n^{4/2} \\
 &= n^2 + n^2 \\
 &= 2n^2 \\
 &\leq c \cdot n^2
 \end{aligned}$$

Thus a valid c is $c = 2$.

Part Three

$$\begin{aligned}
 n^2 - n + 1 &= \\
 &\leq n^2 \\
 &\leq c \cdot n^2/2
 \end{aligned}$$

Thus a valid c is $c = 2$.

Problem 2

Let $\Sigma = \{0, 1\}$. Construct a DFA A that recognizes the language that consists of all binary numbers that can be divided by 5.

Let the state q_k indicate the remainder of k divided by 5. For example, the remainder of 2 would correlate to state q_2 because $7 \bmod 5 = 2$.

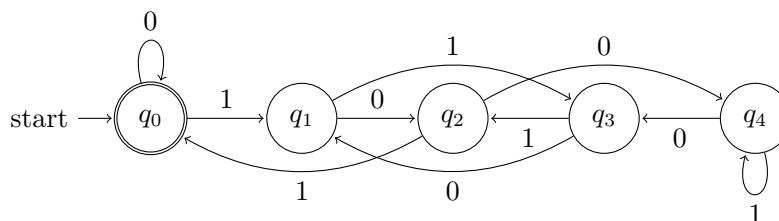


图 1: DFA, A , this is really beautiful, ya know?

Justification

Take a given binary number, x . Since there are only two inputs to our state machine, x can either become $x0$ or $x1$. When a 0 comes into the state machine, it is the same as taking the binary number and multiplying it by two. When a 1 comes into the machine, it is the same as multiplying by two and adding one.

Using this knowledge, we can construct a transition table that tell us where to go:

	$x \bmod 5 = 0$	$x \bmod 5 = 1$	$x \bmod 5 = 2$	$x \bmod 5 = 3$	$x \bmod 5 = 4$
$x0$	0	2	4	1	3
$x1$	1	3	0	2	4

Therefore on state q_0 or $(x \bmod 5 = 0)$, a transition line should go to state q_0 for the input 0 and a line should go to state q_1 for input 1. Continuing this gives us the Figure 1.

Problem 3

伪代码、算法示例，如算法 1所示：

Algorithm 1 Reliable Negative Instances Selection

Input: Positive Instance Set P , Unlabeled Instance Set U , Sample Ratio s .**Output:** Reliable Negative Instance Set RN .

```

1:  $setRN = \emptyset$ 
2: Sample  $s$  of the instances from  $P$  as  $S$ 
3: Set  $P_s = P - S$  with label 1,  $U_s = U \cup S$  with label  $-1$ 
4: Train a classifier  $g$  with  $P_s$  and  $U_s$ 
5: Classify instances in  $U$  using  $g$ , output the class-conditional-probability
6: Select a threshold  $\theta$  according to the class-conditional-probability of instances in  $S$ 
7: for  $d \in U$  do do
8:   if  $Pr(1|d) \leq \theta, RN = RN \cup d$  then
9:     end if
10: end for
11: Output  $RN$ 

```

Problem 4

Suppose we would like to fit a straight line through the origin, i.e., $Y_i = \beta_1 x_i + e_i$ with $i = 1, \dots, n$, $E[e_i] = 0$, and $\text{Var}[e_i] = \sigma_e^2$ and $\text{Cov}[e_i, e_j] = 0, \forall i \neq j$.

Part A

Find the least squares estimator for $\hat{\beta}_1$ for the slope β_1 .

Solution

To find the least squares estimator, we should minimize our Residual Sum of Squares, RSS:

$$\begin{aligned} RSS &= \sum_{i=1}^n (Y_i - \hat{Y}_i)^2 \\ &= \sum_{i=1}^n (Y_i - \hat{\beta}_1 x_i)^2 \end{aligned}$$

By taking the partial derivative in respect to $\hat{\beta}_1$, we get:

$$\frac{\partial}{\partial \hat{\beta}_1} (RSS) = -2 \sum_{i=1}^n x_i (Y_i - \hat{\beta}_1 x_i) = 0$$

This gives us:

$$\begin{aligned} \sum_{i=1}^n x_i (Y_i - \hat{\beta}_1 x_i) &= \sum_{i=1}^n x_i Y_i - \sum_{i=1}^n \hat{\beta}_1 x_i^2 \\ &= \sum_{i=1}^n x_i Y_i - \hat{\beta}_1 \sum_{i=1}^n x_i^2 \end{aligned}$$

Solving for $\hat{\beta}_1$ gives the final estimator for β_1 :

$$\hat{\beta}_1 = \frac{\sum x_i Y_i}{\sum x_i^2}$$

Part B

Calculate the bias and the variance for the estimated slope $\hat{\beta}_1$.

Solution

For the bias, we need to calculate the expected value $E[\hat{\beta}_1]$:

$$\begin{aligned}
 E[\hat{\beta}_1] &= E\left[\frac{\sum x_i Y_i}{\sum x_i^2}\right] \\
 &= \frac{\sum x_i E[Y_i]}{\sum x_i^2} \\
 &= \frac{\sum x_i (\beta_1 x_i)}{\sum x_i^2} \\
 &= \frac{\sum x_i^2 \beta_1}{\sum x_i^2} \\
 &= \beta_1 \frac{\sum x_i^2}{\sum x_i^2} \\
 &= \beta_1
 \end{aligned}$$

Thus since our estimator's expected value is β_1 , we can conclude that the bias of our estimator is 0.

For the variance:

$$\begin{aligned}
 \text{Var}[\hat{\beta}_1] &= \text{Var}\left[\frac{\sum x_i Y_i}{\sum x_i^2}\right] \\
 &= \frac{\sum x_i^2}{\sum x_i^2 \sum x_i^2} \text{Var}[Y_i] \\
 &= \frac{\sum x_i^2}{\sum x_i^2 \sum x_i^2} \text{Var}[Y_i] \\
 &= \frac{1}{\sum x_i^2} \text{Var}[Y_i] \\
 &= \frac{1}{\sum x_i^2} \sigma^2 \\
 &= \frac{\sigma^2}{\sum x_i^2}
 \end{aligned}$$

Problem 5

Prove a polynomial of degree k , $a_k n^k + a_{k-1} n^{k-1} + \dots + a_1 n^1 + a_0 n^0$ is a member of $\Theta(n^k)$ where $a_k \dots a_0$ are nonnegative constants.

证明. To prove that $a_k n^k + a_{k-1} n^{k-1} + \dots + a_1 n^1 + a_0 n^0$, we must show the following:

$$\exists c_1 \exists c_2 \forall n \geq n_0, c_1 \cdot g(n) \leq f(n) \leq c_2 \cdot g(n)$$

For the first inequality, it is easy to see that it holds because no matter what the constants are, $n^k \leq a_k n^k + a_{k-1} n^{k-1} + \dots + a_1 n^1 + a_0 n^0$ even if $c_1 = 1$ and $n_0 = 1$. This is because $n^k \leq c_1 \cdot a_k n^k$ for any nonnegative constant, c_1 and a_k .

Taking the second inequality, we prove it in the following way. By summation, $\sum_{i=0}^k a_i$ will give us a new constant, A . By taking this value of A , we can then do the following:

$$\begin{aligned} a_k n^k + a_{k-1} n^{k-1} + \dots + a_1 n^1 + a_0 n^0 &= \\ &\leq (a_k + a_{k-1} \dots a_1 + a_0) \cdot n^k \\ &= A \cdot n^k \\ &\leq c_2 \cdot n^k \end{aligned}$$

where $n_0 = 1$ and $c_2 = A$. c_2 is just a constant. Thus the proof is complete. □

Problem 18

Evaluate $\sum_{k=1}^5 k^2$ and $\sum_{k=1}^5 (k-1)^2$.

Problem 19

Find the derivative of $f(x) = x^4 + 3x^2 - 2$

Problem 6

Evaluate the integrals $\int_0^1 (1-x^2)dx$ and $\int_1^\infty \frac{1}{x^2}dx$.

Problem 7

表格的示例，单元格内换行示例：

方法	特点	优点	缺点
有监督学习	对数据进行标注， 通过有监督学习的方式 来检测恶意 URL	更强的泛化能力	现实生活中很难获得 精准的标注数据。 在更多时候，我们可能 只得到一小部分恶意 URL 和大量未标记的 URL 样本， 缺乏足够可靠的负例样本
无监督学习	不需要对数据进行标注	无需标注的数据即可进行训练	已知恶意 URL 的标注信息 就难以充分利用，可能 无法达到令人满意的识别能力

Problem 8

插入图片的示例，图片强制在当前位置的示例，如图 2所示：



图 2: ucas-logo

Problem 9

代码的示例：

1
2

```
scheme:[//[user[:password]@]host[:port]][/path][?query][#fragment]
```

Problem 10

引用文献示例:[1] 中提到 balabalaballh

参考文献

- [1] Pawan Prakash, Manish Kumar, Ramana Rao Kompella, and Minaxi Gupta. Phishnet: predictive blacklisting to detect phishing attacks. In *2010 Proceedings IEEE INFOCOM*, pages 1–5. IEEE, 2010.