《课程名称》标题
子标题

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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 $7 \mod 5 = 2$.

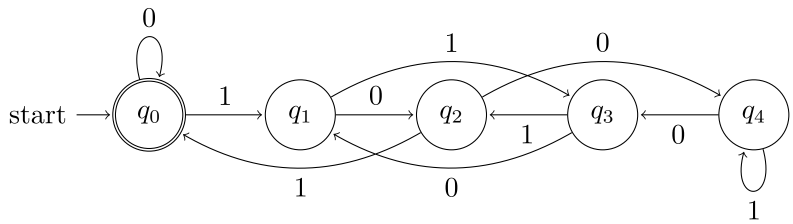

图 1: DFA, A, this is really beautiful, ya know?

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 multipying by two and adding one.

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

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

Therefore on state q_0 or ($x \mod 5 = 0$), 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.

```
setRN = ∅
Sample s of the instances from P as S
Set P_s = P−S with label 1, U_s = U ∪ S with label −1
Train a classifier g with P_s and U_s
Classify instances in U using g, output the class-conditional-probability
Select a threshold θ according to the class-conditional-probability of instances in S
for d ∈ U do do
    if Pr(1|d) ≤ θ, RN = RN ∪ d then
    end if
end for
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 $i = 1, \ldots, n$, $\mathrm{E}[e_i] = 0$, and $\mathrm{Var}[e_i] = \sigma_e^2$ and $\mathrm{Cov}[e_i, e_j] = 0, \forall i \neq j$.

Part A

Find the least squares esimator 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:

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

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 $\mathrm{E}[\hat{\beta}_1]$:

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

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

For the variance:

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

Problem 5

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

证明. To prove that $a_k n^k + a_{k-1} n^{k-1} + \ldots + a_1 n^1 + a_0 n^0$, 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, $n^k \leq a_k n^k + a_{k-1} n^{k-1} + \ldots + a_1 n^1 + a_0 n^0$ 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:

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

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 $\int_0^1 (1-x^2)\mathrm{d}x$ and $\int_1^\infty \frac{1}{x^2}\mathrm{d}x$.

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：

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

Problem 10

引用文献示例:[1] 中提到 balabalabalhh

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.