Anhang A

Die Landauschen Symbole

Die Landauschen Symbole, die auch die O-Notation genannt werden, beschreiben das Wachstumsverhalten von Funktionen. Bei ihnen handelt es sich um Mengen von Funktionen.

$$
\begin{aligned}
O(f(n)) &= \{g(n) \mid \exists c \in \mathbb{R}^+ \exists n_0 \in \mathbb{N} \forall n, n \geq n_0 : |g(n)| \leq c \cdot |f(n)|\} \\
\Omega(f(n)) &= \{g(n) \mid \exists c \in \mathbb{R}^+ \exists n_0 \in \mathbb{N} \forall n, n \geq n_0 : |g(n)| \geq c \cdot |f(n)|\} \\
\Theta(f(n)) &= O(f(n)) \cap \Omega(f(n)) \\
o(f(n)) &= \{g(n) \mid \forall c \in \mathbb{R}^+ \exists n_0 \in \mathbb{N} \forall n, n \geq n_0 : |g(n)| < c \cdot |f(n)|\} \\
\omega(f(n)) &= \{g(n) \mid \forall c \in \mathbb{R}^+ \exists n_0 \in \mathbb{N} \forall n, n \geq n_0 : |g(n)| > c \cdot |f(n)|\}
\end{aligned}
$$

Es hat sich eingebürgert, $g(n) = O(f(n))$ zu schreiben anstelle von $g(n) \in O(f(n))$. Beachte, daß das „=“-Zeichen keine Gleichheit bezeichnet und damit nicht symmetrisch ist! Es darf nur von links nach rechts gelesen werden. D. h. $3n^2 = O(n^3)$ darf man schreiben, aber $O(n^3) = 3n^2$ darf man *nicht* schreiben.

Gleichzeitig sind auch Schreibweisen wie $4n^2 + O(n \log n)$ gebräuchlich, um den konstanten Faktor an dem Term zu zeigen, der am stärksten wächst, und um zu zeigen, daß der Rest der Funktion, der sog. *low order term*, nur noch „unwesentlich“ ist. Ebenso ist dann weiter $4n^2 + O(n \log n) = \Theta(n^2)$ in Gebrauch. $4n^2 + o(n^2)$ wird gerne geschrieben, wenn der *low order term* schwächer als n^2 wächst, aber vielleicht kompliziert hinzuschreiben wäre oder unbekannt ist.

Die Schreibweise $2^{O(f(n))}$ wird ebenfalls benutzt. Sie bezeichnet eine andere Funktionenmenge als $O(2^{f(n)})$, was man sich an $2^{O(\log n)}$ und $O(2^{\log n})$ klarmachen sollte.

Anhang B

Werkzeuge aus der Wahrscheinlichkeitsrechnung

B.1 Satz: (Markov-Ungleichung)
Sei X eine nichtnegative Zufallsvariable. Dann gilt für alle $t > 0$: $\Pr[X \geq t] \leq E[X]/t$.
Mit $t = c \cdot E[X]$ für $c \geq 1$ ergibt sich $\Pr[X \geq c \cdot E[X]] \leq 1/c$.

Beweis:
Sei $t > 0$ gegeben und definiere

$$\tau(x) = \begin{cases} 1 & \text{falls } x/t \geq 1 \\ 0 & \text{sonst.} \end{cases}$$

Es ist $\tau(x) \leq x/t$ für alle $x \geq t$ und $E[\tau(X)] = \Pr[\tau(X) = 1] = \Pr[X/t \geq 1] = \Pr[X \geq t]$. Damit gilt:

$$\Pr[X \geq t] = E[\tau(X)] \leq E[X/t] = E[X]/t \quad ,$$

womit der Satz bewiesen ist. $\square$

B.2 Definition:
Sei $X : \Omega \to \mathbb{R}$ eine Zufallsvariable. Die *Varianz* von X ist

$$\mathrm{Var}[X] = E[(X - E[X])^2] = E[X^2] - E[X]^2 \quad .$$

Die *Standardabweichung* ist $\sigma[X] = \sqrt{\mathrm{Var}[X]}$.

B.3 Satz: (Rechenregeln für die Varianz)
Seien X und Y unabhängige Zufallsvariablen und c eine beliebige Konstante.

(a) $\mathit{Var}[X+Y] = \mathit{Var}[X] + \mathit{Var}[Y]$.

(b) $\mathit{Var}[c \cdot X] = c^2 \cdot \mathit{Var}[X]$.

(c) Ist X eine 0-1-Zufallsvariable, so gilt $\mathit{Var}[X] = E[X] \cdot (1 - E[X])$.

(d) Seien $X_1, \ldots, X_n$ unabhängige Zufallsvariablen, und sei $Z = \prod_{i=1}^n X_i$. Dann ist

$$\frac{\mathit{Var}[Z]}{E[Z]^2} = -1 + \prod_{i=1}^{n}\left(1 + \frac{\mathit{Var}[X_i]}{E[X_i]^2}\right)$$

Der nachfolgende Satz zeigt, wie man mit Hilfe der Varianz ausrechnen kann, wie groß die Wahrscheinlichkeit ist, bei einem Zufallsexperiment „weit“ vom Erwartungswert entfernt zu sein.

B.4 Satz: (Tschebyscheffsche Ungleichung)
Sei X eine Zufallsvariable. Für jedes $\varepsilon > 0$ gilt

$$\Pr[|X - E[X]| \geq \varepsilon] \leq \frac{\mathit{Var}[X]}{\varepsilon^2} \quad .$$

Beweis:

$$\begin{aligned}
\mathrm{Var}[X] &= \sum_{\omega\in\Omega} \big(X(\omega) - E[X]\big)^2 \cdot \Pr[\omega] \quad \geq \sum_{\substack{\omega\in\Omega \\ (X(\omega)-E[X])^2 \geq \varepsilon^2}} \big(X(\omega) - E[X]\big)^2 \cdot \Pr[\omega] \\
&\geq \sum_{\substack{\omega\in\Omega \\ |X(\omega)-E[X]| \geq \varepsilon}} \varepsilon^2 \cdot \Pr[\omega] \quad = \quad \varepsilon^2 \cdot \Pr[|X - E[X]| \geq \varepsilon]
\end{aligned}$$

□

B.5 Korollar:

(a) Für $k > 0$ gilt: $\Pr[|X - E[X]| \geq k \cdot \sigma[X]] \leq \dfrac{1}{k^2}$

(b) Für $\varepsilon' > 0$ gilt: $\Pr[|X - E[X]| \geq \varepsilon' \cdot E[X]] \leq \dfrac{1}{\varepsilon'^2} \cdot \dfrac{\mathit{Var}[X]}{E[X]^2}$

Beweis:
(a) erhält man durch Einsetzen von $\varepsilon = k \cdot \sigma[X]$, (b) durch Einsetzen von $\varepsilon = \varepsilon' \cdot E[X]$. □

Aus der Tschebyscheffschen Ungleichung folgt also $\Pr[|X - E[X]| < 2\sigma] \geq \frac{3}{4}$. D. h. mit ca. 75%iger Sicherheit liegen Zufallsexperimente höchstens um $\pm 2\sigma$ um den Erwartungswert herum.

Die im nächsten Satz erwähnten Chernoff-Schranken führen häufig zu stärkeren Abschätzungen als die Tschebyscheffsche Ungleichung. Eine Sammlung nützlicher Varianten dieser Formel ist der Aufsatz von Hagerup/Rüb [HR90].

B.6 Satz: (Chernoff-Schranken)
Seien $X_1, \ldots, X_n$ unabhängige 0-1-Zufallsvariablen (Poisson-Experimente). Dann gilt für $X = \sum_{i=1}^n X_i$ und $E[X] = \sum_{i=1}^n \Pr[X_i = 1]$ und jedes ε, $0 < \varepsilon \leq 1$:

(a) $\Pr[X < (1-\varepsilon) \cdot E[X]] < \mathrm{e}^{-E[X]\varepsilon^2/2}$

(b) $\Pr[X > (1+\varepsilon) \cdot E[X]] < \mathrm{e}^{-E[X]\varepsilon^2/4}$

(c) (a) und (b) kombiniert ergeben:

$$\begin{aligned}
&\Pr[|X - E[X]| \leq \varepsilon \cdot E[X]] \\
&\quad = \Pr[(1-\varepsilon) \cdot E[X] \leq X \leq (1+\varepsilon) \cdot E[X]] \\
&\quad = 1 - \Pr\left[X < (1-\varepsilon) \cdot E[X] \text{ oder } X > (1+\varepsilon) \cdot E[X]\right] \\
&\quad \geq 1 - 2\mathrm{e}^{-E[X]\varepsilon^2/4}
\end{aligned}$$

Beweis:
Wir beweisen lediglich (a); (b) kann analog beweisen werden.

Für jedes $t > 0$ gilt:

$$\Pr[X < (1-\varepsilon) \cdot E[X]] = \Pr[-X > -(1-\varepsilon) \cdot E[X]] = \Pr[\mathrm{e}^{-tX} > \mathrm{e}^{-t(1-\varepsilon)E[X]}]$$

Mit der Markov-Ungleichung (Satz B.1) und der Unabhängigkeit der X_i ergibt sich

$$\begin{aligned}
\Pr[\mathrm{e}^{-tX} > \mathrm{e}^{-t(1-\varepsilon)E[X]}] &\leq \frac{E[\mathrm{e}^{-tX}]}{\mathrm{e}^{-t(1-\varepsilon)E[X]}} \\
&= \mathrm{e}^{t(1-\varepsilon)E[X]} \cdot E\left[\prod_{i=1}^n \mathrm{e}^{-tX_i}\right] = \mathrm{e}^{t(1-\varepsilon)E[X]} \cdot \prod_{i=1}^n E[\mathrm{e}^{-tX_i}] \\
&= \mathrm{e}^{t(1-\varepsilon)E[X]} \cdot \prod_{i=1}^n \Big(\Pr[X_i = 1]\mathrm{e}^{-t} + (1 - \Pr[X_i = 1])\Big) \\
&= \mathrm{e}^{t(1-\varepsilon)E[X]} \cdot \prod_{i=1}^n \Big(1 + \Pr[X_i = 1](\mathrm{e}^{-t} - 1)\Big)
\end{aligned}$$

Nun wählen wir $t = -\ln(1-\varepsilon)$ und benutzen, daß $1 - x < \mathrm{e}^{-x}$ („gewöhnliche" Reihenentwicklung für e^x) ist, so daß wir bekommen:

$$\begin{aligned}
\Pr[X < (1-\varepsilon)\cdot E[X]] &\leq (1-\varepsilon)^{-(1-\varepsilon)E[X]} \cdot \prod_{i=1}^{n}(1-\varepsilon \Pr[X_i = 1]) \\
&< (1-\varepsilon)^{-(1-\varepsilon)E[X]} \cdot \prod_{i=1}^{n} \mathrm{e}^{-\varepsilon \Pr[X_i=1]} \\
&= (1-\varepsilon)^{-(1-\varepsilon)E[X]} \cdot \mathrm{e}^{\sum_{i=1}^{n} -\varepsilon \Pr[X_i=1]} = \left((1-\varepsilon)^{-(1-\varepsilon)} \cdot \mathrm{e}^{-\varepsilon}\right)^{E[X]}
\end{aligned}$$

Schließlich benutzen wir, daß $(1-\varepsilon)^{-(1-\varepsilon)} < \mathrm{e}^{\varepsilon - \varepsilon^2/2}$ für $0 < \varepsilon \leq 1$ ist (Anfang der McLaurin-Reihe für $\ln(1-\varepsilon) = -(\varepsilon + \frac{1}{2}\varepsilon^2 + \cdots)$), und erhalten damit direkt die Aussage (a). □

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Index