## Markov $L_2$ -inequality with the Laguerre Weight

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Let  $w_{\alpha}(x) := x^{\alpha} e^{-x}$ , where  $\alpha > -1$ , be the Laguerre weight function, and let  $\|\cdot\|_{w_{\alpha}}$  be the associated  $L_2$ -norm,

$$||f||_{w_{\alpha}} = \left(\int_{0}^{\infty} |f(x)|^{2} w_{\alpha}(x) dx\right)^{1/2}.$$

By  $\mathcal{P}_n$  we denote the set of algebraic polynomials of degree  $\leq n$ . We study the best constant  $c_n(\alpha)$  in the Markov inequality in this norm

$$||p'_n||_{w_\alpha} \le c_n(\alpha)||p_n||_{w_\alpha}, \qquad p_n \in \mathcal{P}_n,$$

namely the constant

$$c_n(\alpha) := \sup_{p_n \in \mathcal{P}_n} \frac{\|p'_n\|_{w_\alpha}}{\|p_n\|_{w_\alpha}}.$$

We derive explicit lower and upper bounds for the Markov constant  $c_n(\alpha)$ , as well as for the asymptotic Markov constant

$$c(\alpha) = \lim_{n \to \infty} \frac{c_n(\alpha)}{n}$$
.

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### 1. Introduction and Statement of the Results

Let  $w_{\alpha}(x) := x^{\alpha} x^{-x}$ , where  $\alpha > -1$ , be the Laguerre weight function, and let  $\|\cdot\|_{w_{\alpha}}$  be the associated  $L_2$ -norm,

$$||f||_{w_{\alpha}} = \left(\int_{0}^{\infty} |f(x)|^{2} w_{\alpha}(x) dx\right)^{1/2}.$$

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By  $\mathcal{P}_n$  we denote the set of algebraic polynomials of degree at most n. We study here the best constant  $c_n(\alpha)$  in the Markov inequality in this norm

$$||p_n'||_{w_\alpha} \le c_n(\alpha)||p_n||_{w_\alpha}, \qquad p_n \in \mathcal{P}_n,$$
(1.1)

namely the constant

$$c_n(\alpha) := \sup_{p_n \in \mathcal{P}_n} \frac{\|p'_n\|_{w_\alpha}}{\|p_n\|_{w_\alpha}}.$$

Our goal is to obtain *good* and *explicit* lower and upper bounds for  $c_n(\alpha)$ , i.e., to find constants  $\underline{c}(n,\alpha)$  and  $\overline{c}(n,\alpha)$  such that

$$\underline{c}(n,\alpha) \le c_n(\alpha) \le \overline{c}(n,\alpha)$$
,

with a small ratio  $\frac{\overline{c}(n,\alpha)}{\underline{c}(n,\alpha)}$ . Before formulating our results here, let us give a brief account on the results hitherto known.

It is only the case  $\alpha=0$  where the best Markov constant is known, namely, Turán [6] proved that

$$c_n(0) = \left(2\sin\frac{\pi}{4n+2}\right)^{-1}.$$

Dörfler [1] showed that  $c_n(\alpha) = \mathcal{O}(n)$  for every fixed  $\alpha > -1$  by proving the estimates

$$c_n^2(\alpha) \ge \frac{n^2}{(\alpha+1)(\alpha+3)} + \frac{(2\alpha^2 + 5\alpha + 6)n}{3(\alpha+1)(\alpha+2)(\alpha+3)} + \frac{\alpha+6}{3(\alpha+2)(\alpha+3)}, \quad (1.2)$$

$$c_n^2(\alpha) \le \frac{n(n+1)}{2(\alpha+1)},\tag{1.3}$$

see [2] for a more accessible source. In the same paper, [2], Dörfler proved for the asymptotic constant  $c(\alpha) = \lim_{\alpha \to \infty} \frac{c_n(\alpha)}{n}$  that

$$c(\alpha) := \lim_{n \to \infty} \frac{c_n(\alpha)}{n} = \frac{1}{j_{(\alpha-1)/2,1}}, \qquad (1.4)$$

where  $j_{\nu,1}$  is the first positive zero of the Bessel function  $J_{\nu}(z)$ .

In a recent paper [3] we proved the following statement.

**Theorem A ([3, Theorem 1]).** For all  $\alpha > -1$  and  $n \in \mathbb{N}$ ,  $n \geq 3$ , the best constant  $c_n(\alpha)$  in the Markov inequality

$$||p'||_{w_{\alpha}} \le c_n(\alpha) ||p||_{w_{\alpha}}, \quad p \in \mathcal{P}_n,$$

admits the estimates

$$\frac{2(n+\frac{2\alpha}{3})(n-\frac{\alpha+1}{6})}{(\alpha+1)(\alpha+5)} < c_n^2(\alpha) < \frac{(n+1)(n+\frac{2(\alpha+1)}{5})}{(\alpha+1)((\alpha+3)(\alpha+5))^{1/3}},$$
(1.5)

where for the left-hand side inequality it is additionally assumed that  $n > \frac{\alpha+1}{6}$ .

209

Clearly, Theorem A implies some inequalities for the asymptotic Markov constant  $c(\alpha)$  and, through (1.4), inequalities for  $j_{\nu,1}$ , the first positive zero of the Bessel function  $J_{\nu}$  (see [3, Corollaries 1, 3]).

We also proved in [3, Theorem 2] that  $c(\alpha) = \mathcal{O}(\alpha^{-1})$ , which shows that the upper estimate for  $c_n(\alpha)$  in (1.5), though rather good for moderate  $\alpha$ , is not optimal.

Our approach here is based on the norm estimates of a related positive definite matrix  $\mathbf{A}_n$ . In [4] the same approach has been applied for derivation of bounds for the best Markov constant in the  $L_2$  Markov inequality with the Gegenbauer weight.

Our main result is an upper bound for  $c_n(\alpha)$  which is of the right order with respect to both n and  $\alpha$  as they grow to infinity.

**Theorem 1.1.** For all  $n \in \mathbb{N}$ ,  $n \geq 3$ , the best constant  $c_n(\alpha)$  in the Markov inequality (1.1) satisfies the inequality

$$c_n^2(\alpha) \le \frac{4n(n+2+\frac{3(\alpha+1)}{4})}{\alpha^2+10\alpha+8}, \qquad \alpha \ge 2.$$

As a consequence of Theorem 1.1 and Dörfler's lower bound (1.2) for  $c_n(\alpha)$  we show that

$$c_n^2(\alpha) \approx \frac{n(n+\alpha+3)}{(\alpha+1)(\alpha+8)}, \qquad n \ge 3, \ \alpha \ge 2.$$

**Corollary 1.1.** For all  $\alpha \geq 2$  and  $n \geq 3$  the best constant  $c_n(\alpha)$  in the Markov inequality (1.1) satisfies

$$\frac{2n(n+\alpha+3)}{3(\alpha+1)(\alpha+8)} \le c_n^2(\alpha) \le \frac{4n(n+\alpha+3)}{(\alpha+1)(\alpha+8)}.$$

As another consequence, we find the limit value of  $(\alpha+1)c_n^2(\alpha)$  as  $\alpha$  tends to -1, and obtain asymptotic estimates for  $\alpha c_n^2(\alpha)$  as  $\alpha$  tends to infinity.

Corollary 1.2. The best constant  $c_n(\alpha)$  in the Markov inequality (1.1) satisfies:

(i) 
$$\lim_{\substack{\alpha \to -1 \\ 2n}} (\alpha+1)c_n^2(\alpha) = \frac{n(n+1)}{2};$$

(ii) 
$$\frac{2n}{3} \le \lim_{\alpha \to \infty} \alpha c_n^2(\alpha) \le 3n$$
.

Finally, Theorem 1.1 provides an upper bound for the asymptotic Markov constant  $c(\alpha)$  which is of the correct order  $O(\alpha^{-1})$  as  $\alpha$  tends to infinity. As a consequence of Theorem A and Theorem 1.1 we have the following

Corollary 1.3. The asymptotic Markov constant  $c(\alpha) = \lim_{n \to \infty} n^{-1}c_n(\alpha)$  satisfies the inequalities

$$\frac{2}{(\alpha+1)(\alpha+5)} < c^{2}(\alpha) < \begin{cases} \frac{1}{(\alpha+1)\sqrt[3]{(\alpha+3)(\alpha+5)}}, & -1 < \alpha \le \alpha^{*}, \\ \frac{4}{\alpha^{2}+10\alpha+8}, & \alpha > \alpha^{*}, \end{cases}$$

where  $\alpha^* \approx 43.4$ 

It is worth noticing here that, for all  $\alpha > -1$ , the ratio of the upper and the lower bound for  $c(\alpha)$  in Corollary 1.3 is less than  $\sqrt{2}$ .

The rest of the paper is organized as follows. Sect. 2 contains a brief characterization of the squared best Markov constant  $c_n^2(\alpha)$  as the largest eigenvalue of a specific matrix  $\mathbf{A}_n$ . In Sect. 3 we prove some estimates for ratios of Gamma functions needed for the proof of Theorem 1.1. The proof of Theorem 1.1 is given in Sect. 4. Sect. 5 is concerned with the evaluation of  $\|\mathbf{A}_n\|_F$ , the Frobenius norm of  $\mathbf{A}_n$ , and the bounds for  $c_n(\alpha)$  implied thereby; in particular, we reproduce Dörfler's lower bound (1.2). The proof of Corollaries 1.1–1.3 is given in Sect. 6.

### 2. Preliminaries

It is well-known that the squared best Markov constant  $c_n^2(\alpha)$  equals to the largest eigenvalue of a certain positive definite matrix  $\mathbf{A}_n$ . Here we derive the explicit form of  $\mathbf{A}_n$ .

The orthogonal polynomials with respect to the Laguerre weight function  $w_{\alpha}(x) = x^{\alpha}e^{-x}$ ,  $x \in \mathbb{R}_{+}$ , are Laguerre polynomials  $\{L_{m}^{(\alpha)}\}_{m \in \mathbb{N}_{0}}$ , with the standard normalization

$$||L_m^{\alpha}||_{w_{\alpha}} = \left(\frac{\Gamma(m+\alpha+1)}{\Gamma(m+1)}\right)^{1/2} =: \beta_{m+1}, \qquad m \in \mathbb{N}_0$$
 (2.1)

(for simplicity sake, we suppress the dependance of the  $\beta$ 's on  $\alpha$ ). Further specific properties of the Laguerre polynomials are (see, e.g., [5, eqs. (5.1.13), (5.1.14)])

$$\frac{d}{dx}L_m^{(\alpha)}(x) = -L_{m-1}^{(\alpha+1)}(x), \qquad m \in \mathbb{N},$$
 (2.2)

$$L_m^{(\alpha+1)}(x) = \sum_{\nu=0}^m L_\nu^{(\alpha)}(x).$$
 (2.3)

Assume that  $\hat{p}_n \in \mathcal{P}_n$ ,  $\|\hat{p}_n\|_{w_\alpha} = 1$ , is an extreme polynomial in the  $L_2$  Markov inequality (1.1), i.e.,

$$\sup\{\|p'\|_{w_{\alpha}}^{2}: p \in \mathcal{P}_{n}, \|p\|_{w_{\alpha}} = 1\} = c_{n}^{2}(\alpha) = \|\hat{p}_{n}'\|_{w_{\alpha}}^{2}.$$
 (2.4)

Without loss of generality,  $\hat{p}_n$  can be represented in the form

$$\hat{p}_n = \sum_{\nu=1}^n a_{\nu} L_{\nu}^{(\alpha)}, \quad a_{\nu} \in \mathbb{R}, \quad 1 \le \nu \le n,$$

then

$$\|\hat{p}_n\|_{w_\alpha}^2 = \sum_{\nu=1}^n a_\nu^2 \beta_{\nu+1}^2 =: \sum_{\nu=1}^n t_\nu^2 =: \|\mathbf{t}\|^2 = 1,$$

where  $\mathbf{t} = (t_1, \dots, t_n)^{\top} \in \mathbb{R}^n$  and  $\|\cdot\|$  is the Euclidean norm in  $\mathbb{R}^n$ , i.e.,  $\|\mathbf{t}\|^2 = \mathbf{t}^{\top} \mathbf{t}$ .

By (2.1), (2.2) and (2.3), we get

$$\|\hat{p}_{n}'\|_{w_{\alpha}}^{2} = \left\| \sum_{\nu=1}^{n} a_{\nu} \left( \sum_{\mu=0}^{\nu-1} L_{\mu}^{(\alpha)} \right) \right\|_{w_{\alpha}}^{2} = \left\| \sum_{\mu=1}^{n} \left( \sum_{\nu=\mu}^{n} a_{\nu} \right) L_{\mu-1} \right\|_{w_{\alpha}}^{2}$$
$$= \sum_{\mu=1}^{n} \left( \sum_{\nu=\mu}^{n} \frac{\beta_{\mu}}{\beta_{\nu+1}} t_{\nu} \right)^{2} = \|\mathbf{C}_{n} \mathbf{t}\|^{2},$$

where  $\mathbf{C}_n$  is the upper triangular  $n \times n$  matrix

$$\mathbf{C}_{n} = \begin{pmatrix} \frac{\beta_{1}}{\beta_{2}} & \frac{\beta_{1}}{\beta_{3}} & \cdots & \frac{\beta_{1}}{\beta_{n+1}} \\ 0 & \frac{\beta_{2}}{\beta_{3}} & \cdots & \frac{\beta_{2}}{\beta_{n+1}} \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \frac{\beta_{n}}{\beta_{n+1}} \end{pmatrix}.$$

Hence, (2.4) admits the equivalent formulation

$$c_n^2(\alpha) = \sup_{\substack{\mathbf{t} \in \mathbb{R}^n \\ \|\mathbf{t}\| = 1}} \|\mathbf{C}_n \mathbf{t}\|^2 = \sup_{\substack{\mathbf{t} \in \mathbb{R}^n \\ \|\mathbf{t}\| = 1}} \mathbf{t}^\top \mathbf{C}_n^\top \mathbf{C}_n \mathbf{t} = \mu_{\max}(\mathbf{A}_n),$$

where  $\mu_{\max}(\mathbf{A}_n)$  is the largest eigenvalue of the positive definite matrix

$$\mathbf{A}_n := \mathbf{C}_n^{\top} \mathbf{C}_n$$
.

After a straightforward calculation we find

$$\mathbf{A}_{n} = \begin{pmatrix} \frac{\beta_{1}^{2}}{\beta_{2}^{2}} & \frac{\beta_{1}^{2}}{\beta_{2}\beta_{3}} & \frac{\beta_{1}^{2}}{\beta_{2}\beta_{4}} & \cdots & \frac{\beta_{1}^{2}}{\beta_{2}\beta_{n+1}} \\ \frac{\beta_{1}^{2}}{\beta_{2}\beta_{3}} & \frac{1}{\beta_{3}^{2}} \left( \sum_{j=1}^{2} \beta_{j}^{2} \right) & \frac{1}{\beta_{3}\beta_{4}} \left( \sum_{j=1}^{2} \beta_{j}^{2} \right) & \cdots & \frac{1}{\beta_{3}\beta_{n+1}} \left( \sum_{j=1}^{2} \beta_{j}^{2} \right) \\ \frac{\beta_{1}^{2}}{\beta_{2}\beta_{4}} & \frac{1}{\beta_{3}\beta_{4}} \left( \sum_{j=1}^{2} \beta_{j}^{2} \right) & \frac{1}{\beta_{4}^{2}} \left( \sum_{j=1}^{3} \beta_{j}^{2} \right) & \cdots & \frac{1}{\beta_{4}\beta_{n+1}} \left( \sum_{j=1}^{3} \beta_{j}^{2} \right) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \frac{\beta_{1}^{2}}{\beta_{2}\beta_{n+1}} & \frac{1}{\beta_{3}\beta_{n+1}} \left( \sum_{j=1}^{2} \beta_{j}^{2} \right) & \frac{1}{\beta_{4}\beta_{n+1}} \left( \sum_{j=1}^{3} \beta_{j}^{2} \right) & \cdots & \frac{1}{\beta_{n+1}^{2}} \left( \sum_{j=1}^{n} \beta_{j}^{2} \right) \end{pmatrix}.$$

We observe that the elements  $a_{k,i}$  of the matrix  $\mathbf{A}_n$  are given by

$$a_{k,i} = \frac{1}{\beta_{i+1}\beta_{k+1}} \sum_{j=1}^{\min\{k,i\}} \beta_j^2 = \begin{cases} \frac{\beta_{i+1}}{\beta_{k+1}} \left( \frac{1}{\beta_{i+1}^2} \sum_{j=1}^i \beta_j^2 \right), & i \leq k, \\ \frac{\beta_{k+1}}{\beta_{i+1}} \left( \frac{1}{\beta_{k+1}^2} \sum_{j=1}^k \beta_j^2 \right), & i \geq k, \end{cases}$$

so that

$$a_{k,k} = \frac{1}{\beta_{k+1}^2} \sum_{j=1}^k \beta_j^2, \qquad a_{k,i} = \begin{cases} \frac{\beta_{i+1}}{\beta_{k+1}} a_{i,i}, & i \le k, \\ \frac{\beta_{k+1}}{\beta_{i+1}} a_{k,k}, & i \ge k. \end{cases}$$
 (2.5)

Hence,  $\mathbf{A}_n$  can be written in the following simplified form

$$\mathbf{A}_{n} = \begin{pmatrix} a_{11} & \frac{\beta_{2}}{\beta_{3}} a_{11} & \frac{\beta_{2}}{\beta_{4}} a_{11} & \cdots & \frac{\beta_{2}}{\beta_{n+1}} a_{11} \\ \frac{\beta_{2}}{\beta_{3}} a_{11} & a_{22} & \frac{\beta_{3}}{\beta_{4}} a_{22} & \cdots & \frac{\beta_{3}}{\beta_{n+1}} a_{22} \\ \frac{\beta_{2}}{\beta_{4}} a_{11} & \frac{\beta_{3}}{\beta_{4}} a_{22} & a_{33} & \cdots & \frac{\beta_{4}}{\beta_{n+1}} a_{33} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \frac{\beta_{2}}{\beta_{n+1}} a_{11} & \frac{\beta_{3}}{\beta_{n+1}} a_{22} & \frac{\beta_{4}}{\beta_{n+1}} a_{33} & \cdots & a_{nn} \end{pmatrix} . \tag{2.6}$$

We complete this section with giving explicit formulae for  $a_{k,k}$  and the trace of  $\mathbf{A}_n$ .

**Proposition 2.1.** For every  $k \in \mathbb{N}$  and  $\alpha > -1$ ,

$$a_{k,k} = \frac{k}{\alpha + 1}$$

and consequently

$$\operatorname{tr}(\mathbf{A}_n) = \frac{n(n+1)}{2(\alpha+1)}.$$

*Proof.* In view of (2.5), we need to show that

$$\frac{1}{\beta_{k+1}^2} \sum_{j=1}^k \beta_j^2 = \frac{k}{\alpha+1} \,. \tag{2.7}$$

The proof is by induction with respect to k. Since

$$\frac{\beta_k^2}{\beta_{k+1}^2} = \frac{\frac{\Gamma(k+\alpha)}{\Gamma(k)}}{\frac{\Gamma(k+1+\alpha)}{\Gamma(k+1)}} = \frac{k}{k+\alpha},$$

(2.7) is true for k = 1. Assuming that (2.7) is true for  $k - 1 \in \mathbb{N}$ , we obtain

$$\frac{1}{\beta_{k+1}^2} \sum_{i=1}^k \beta_j^2 = \frac{\beta_k^2}{\beta_{k+1}^2} + \frac{\beta_k^2}{\beta_{k+1}^2} \left( \frac{1}{\beta_k^2} \sum_{i=1}^{k-1} \beta_j^2 \right) = \frac{k}{k+\alpha} \left( 1 + \frac{k-1}{\alpha+1} \right) = \frac{k}{\alpha+1}.$$

Hence, the induction step is performed, and the proof of (2.7) is complete.  $\Box$ 

213

Remark 2.1. Dörfler's upper estimate (1.3) is simply the inequality

$$c_n^2(\alpha) = \mu_{\max}(\mathbf{A}_n) \le \operatorname{tr}(\mathbf{A}_n) = \frac{n(n+1)}{2(\alpha+1)}.$$

# 3. Estimates for $\frac{\beta_i}{\beta_k}$

We shall need estimates for the elements  $a_{k,i}$ ,  $k \neq i$ , of the matrix  $\mathbf{A}_n$  in (2.6), and this requires estimates for the ratios of the  $\beta$ 's. We prove the following lemma.

**Lemma 3.1.** For every  $\alpha \geq 1$  and  $i, k \in \mathbb{N}$ , i < k, there holds

$$\frac{\frac{\Gamma(i+\alpha)}{\Gamma(i)}}{\frac{\Gamma(k+\alpha)}{\Gamma(k)}} \leq \left(\frac{i+\frac{\alpha-1}{2}}{k+\frac{\alpha-1}{2}}\right)^{\alpha}.$$

*Proof.* It suffices to prove only the case k=i+1, for then the general case will follow from

$$\frac{\frac{\Gamma(i+\alpha)}{\Gamma(i)}}{\frac{\Gamma(k+\alpha)}{\Gamma(k)}} = \prod_{\nu=i}^{k-1} \frac{\frac{\Gamma(\nu+\alpha)}{\Gamma(\nu)}}{\frac{\Gamma(\nu+1+\alpha)}{\Gamma(\nu+1)}}, \qquad \frac{i+\frac{\alpha-1}{2}}{k+\frac{\alpha-1}{2}} = \prod_{\nu=i}^{k-1} \frac{\nu+\frac{\alpha-1}{2}}{\nu+1+\frac{\alpha-1}{2}}.$$

Thus, we need to show that

$$\frac{i}{i+\alpha} \le \left(\frac{i+\frac{\alpha-1}{2}}{i+1+\frac{\alpha-1}{2}}\right)^{\alpha}, \qquad i \ge 1, \ \alpha \ge 1,$$

or, equivalently,

$$\left(1 + \frac{1}{i + \frac{\alpha - 1}{2}}\right)^{\alpha} \le 1 + \frac{\alpha}{i} \,.$$
(3.1)

Clearly, (3.1) turns into identity when  $\alpha = 1$ , so we assume further that  $\alpha > 1$ . Set

$$z = \frac{1}{i + \frac{\alpha - 1}{2}} \,, \qquad 0 < z \le \frac{2}{\alpha + 1} < 1 \,,$$

then

$$i = \frac{2 - (\alpha - 1)z}{2z} \,,$$

and inequality (3.1) becomes

$$(1+z)^{\alpha} \le 1 + \frac{2\alpha z}{2 - (\alpha - 1)z}, \qquad 0 < z \le \frac{2}{\alpha + 1} < 1, \quad \alpha > 1.$$

Assume that  $m-1 < \alpha \leq m$ , where  $m \in \mathbb{N}, m \geq 2$ . By Maclaurin's formula, we have

$$(1+z)^{\alpha} \le 1 + \sum_{\nu=1}^{m} \frac{\alpha(\alpha-1)\dots(\alpha-\nu+1)}{\nu!} z^{\nu}$$

and it suffices to show that

$$\sum_{\nu=1}^{m} \frac{\alpha(\alpha-1)\dots(\alpha-\nu+1)}{\nu!} z^{\nu} \le \frac{2\alpha z}{2-(\alpha-1)z}.$$

Multiplying both sides of this inequality by  $2 - (\alpha - 1)z > 0$  and arranging the powers of z, we arrive at the equivalent inequality

$$\sum_{\nu=2}^{m+1} \frac{(2-\nu)(\alpha+1)\alpha(\alpha-1)\dots(\alpha-\nu+2)}{\nu!} z^{\nu} =: \sum_{\nu=2}^{m+1} a_{\nu} z^{\nu} \le 0,$$

which is obviously true since z > 0 and  $a_{\nu} \le 0, \ 2 \le \nu \le m+1.$ 

Lemma 3.1 is a particular case of the following more general statement, which is of independent interest.

**Proposition 3.1.** Let  $i, k \in \mathbb{N}$ , i < k.

(i) If  $-1 < \alpha \le 0$  or  $\alpha \ge 1$ , then

$$\left(\frac{i}{k}\right)^{\alpha} \leq \frac{\frac{\Gamma(i+\alpha)}{\Gamma(i)}}{\frac{\Gamma(k+\alpha)}{\Gamma(k)}} \leq \left(\frac{i+\frac{\alpha-1}{2}}{k+\frac{\alpha-1}{2}}\right)^{\alpha}.$$

(ii) If  $0 \le \alpha \le 1$ , then

$$\left(\frac{i}{k}\right)^{\alpha} \geq \frac{\frac{\Gamma(i+\alpha)}{\Gamma(i)}}{\frac{\Gamma(k+\alpha)}{\Gamma(k)}} \geq \left(\frac{i+\frac{\alpha-1}{2}}{k+\frac{\alpha-1}{2}}\right)^{\alpha}.$$

The proof of Proposition 3.1 is omitted as we only need its part given in Lemma 3.1.

### 4. Proof of Theorem 1.1

As was mentioned in Sect. 2,  $c_n^2(\alpha) = \mu_{\max}(\mathbf{A}_n)$ , where  $\mu_{\max}(\mathbf{A}_n)$  is the largest eigenvalue of the matrix  $\mathbf{A}_n$  given by (2.6). It is well-known that

$$\mu_{\max}(\mathbf{A}_n) \le \|\mathbf{A}_n\|_*,$$

where  $\|\cdot\|_*$  is any matrix norm. Here, we shall exploit  $\|\cdot\|_{\infty}$ ,

$$\|\mathbf{A}_n\|_{\infty} = \max_{1 \le k \le n} \sum_{i=1}^n |a_{k,i}| = \max_{1 \le k \le n} \sum_{i=1}^n a_{k,i}$$

(notice that  $a_{k,i} > 0$ ,  $1 \le i, k \le n$ ). Theorem 1.1 is an immediate consequence of the following statement.

**Proposition 4.1.** The following inequality holds true:

$$\|\mathbf{A}_n\|_{\infty} \le \frac{4n\left(n+2+\frac{3(\alpha+1)}{4}\right)}{\alpha^2+10\alpha+8}, \qquad \alpha \ge 2.$$

We shall need the following lemma, which is proved in [4].

**Lemma 4.1.** Let  $\alpha_i > 0$ ,  $\gamma_{\min} \leq \gamma_i \leq \gamma_{\max}$ ,  $1 \leq i \leq r$ , and let

$$f(x) := (x + \gamma_1)^{\alpha_1} (x + \gamma_2)^{\alpha_2} \cdots (x + \gamma_r)^{\alpha_r}, \qquad s := \sum_{i=1}^r \alpha_i.$$

Then, for any  $x > x_0$ , where  $x_0 + \gamma_{\min} \ge 0$ , we have

$$\frac{1}{s+1} \left[ (t + \gamma_{\min}) f(t) \right]_{x_0}^x < \int_{x_0}^x f(t) \, dt < \frac{1}{s+1} \left( (x + \gamma_{\max}) f(x) \right).$$

Proof of Proposition 4.1. Let us assume first that  $\alpha > 2$ . For a fixed k,  $1 \le i, k \le n$ , we consider the sum of the elements in the k-th row of  $\mathbf{A}_n$ ,

$$\sum_{i=1}^{n} a_{k,i} = \sum_{i=1}^{k-1} \frac{\beta_{i+1}}{\beta_{k+1}} a_{i,i} + a_{k,k} + \sum_{i=k+1}^{n} \frac{\beta_{k+1}}{\beta_{i+1}} a_{k,k}.$$

By Lemma 2.1 and Lemma 3.1, we have

$$a_{\nu,\nu} = \frac{\nu}{1+\alpha}, \qquad \frac{\beta_{\mu+1}}{\beta_{\nu+1}} \le \left(\frac{\mu + \frac{\alpha+1}{2}}{\nu + \frac{\alpha+1}{2}}\right)^{\alpha/2}, \qquad \mu < \nu, \quad \alpha \ge 1,$$

hence

$$\sum_{i=1}^{n} a_{k,i} \le \frac{1}{1+\alpha} \left[ \left( k + \frac{\alpha+1}{2} \right)^{-\alpha/2} \sum_{i=1}^{k-1} i \left( i + \frac{\alpha+1}{2} \right)^{\alpha/2} + k + k \left( k + \frac{\alpha+1}{2} \right)^{\alpha/2} \sum_{i=k+1}^{n} \left( i + \frac{\alpha+1}{2} \right)^{-\alpha/2} \right]$$

$$=: \frac{1}{1+\alpha} \left[ \left( k + \frac{\alpha+1}{2} \right)^{-\alpha/2} S_1 + k + k \left( k + \frac{\alpha+1}{2} \right)^{\alpha/2} S_2 \right].$$

To obtain an upper bound for  $S_1$ , we observe that  $f_1(x) = x\left(x + \frac{\alpha+1}{2}\right)^{\alpha/2}$  is an increasing function in  $(0, \infty)$ , hence we can estimate the sum by an integral and then estimate the integral with the help of Lemma 4.1. This yields

$$S_1 \le \int_0^k f_1(x) \, dx < \frac{1}{\frac{\alpha}{2} + 2} \, k \left( k + \frac{\alpha + 1}{2} \right)^{\alpha/2 + 1} = \frac{2}{\alpha + 4} \, k \left( k + \frac{\alpha + 1}{2} \right)^{\alpha/2 + 1}.$$

To estimate  $S_2$  from above, we observe that  $f_2(x) = \left(x + \frac{\alpha+1}{2}\right)^{-\alpha/2}$  is a decreasing function in  $(0, \infty)$ , hence

$$S_2 \le \int_k^n f_2(x) \, dx = \frac{2}{\alpha - 2} \left( k + \frac{\alpha + 1}{2} \right)^{1 - \alpha/2} \left[ 1 - \left( \frac{k + \frac{\alpha + 1}{2}}{n + \frac{\alpha + 1}{2}} \right)^{\alpha/2 - 1} \right].$$

Substituting the above upper bounds for  $S_1$  and  $S_2$ , we obtain

$$\sum_{i=1}^{n} a_{k,i} \leq \frac{2k\left(k + \frac{\alpha+1}{2}\right)}{(\alpha+1)(\alpha-2)} \left[ \frac{2(\alpha+1)}{\alpha+4} - \left(\frac{k + \frac{\alpha+1}{2}}{n + \frac{\alpha+1}{2}}\right)^{\alpha/2 - 1} \right] + \frac{k}{\alpha+1}$$

$$=: \frac{k}{\alpha+1} + \frac{2\left(n + \frac{\alpha+1}{2}\right)^2}{(\alpha+1)(\alpha-2)} \psi_{\alpha}(k)\varphi_{\alpha}(y), \qquad (4.1)$$

where

$$\varphi_{\alpha}(y) := \frac{2(\alpha+1)}{\alpha+4} y^2 - y^{\alpha/2+1}, \qquad y := \frac{k + \frac{\alpha+1}{2}}{n + \frac{\alpha+1}{2}} \in (0,1],$$
$$\psi_{\alpha}(k) := \frac{k}{k + \frac{\alpha+1}{2}},$$

For a fixed  $\alpha > 2$ , the function  $\varphi_{\alpha}$  has a unique local extremum in [0, 1], a maximum, which is attained at

$$y_{\alpha} = \left(\frac{8(\alpha+1)}{(\alpha+2)(\alpha+4)}\right)^{2/(\alpha-2)} = \left(1 - \frac{\alpha(\alpha-2)}{(\alpha+2)(\alpha+4)}\right)^{2/(\alpha-2)} \in (0,1) \quad (4.2)$$

and

$$\max_{y \in [0,1]} \varphi_{\alpha}(y) = \varphi_{\alpha}(y_{\alpha}) = \frac{2(\alpha+1)(\alpha-2)}{(\alpha+2)(\alpha+4)} y_{\alpha}^{2} > 0.$$
 (4.3)

We proceed with a further estimation of  $y_{\alpha}^2$ . From (4.2) and  $\ln(1+x) \leq x$ , x > -1, we have

$$\ln y_{\alpha}^2 = \frac{4}{\alpha - 2} \ln \left( 1 - \frac{\alpha(\alpha - 2)}{(\alpha + 2)(\alpha + 4)} \right) < -\frac{4\alpha}{(\alpha + 2)(\alpha + 4)},$$

hence

$$y_{\alpha}^{2} \le e^{-\frac{4\alpha}{(\alpha+2)(\alpha+4)}} \le \frac{1}{1 + \frac{4\alpha}{(\alpha+2)(\alpha+4)}} = \frac{(\alpha+2)(\alpha+4)}{\alpha^{2} + 10\alpha + 8},$$

where for the last inequality we have used that  $e^{-x} \leq \frac{1}{1+x}$ ,  $x \geq 0$ . Replacing this bound in (4.3), we obtain

$$\max_{y \in [0,1]} \varphi_{\alpha}(y) \le \frac{2(\alpha+1)(\alpha-2)}{\alpha^2 + 10\alpha + 8}.$$

This estimate and

$$\max_{1 \le k \le n} \psi_{\alpha}(k) = \psi_{\alpha}(n) = \frac{n}{n + \frac{\alpha + 1}{2}}$$

yield

$$\frac{2\left(n+\frac{\alpha+1}{2}\right)^2}{(\alpha+1)(\alpha-2)} \max_{y \in [0,1]} \varphi_{\alpha}(y) \max_{1 \le k \le n} \psi_{\alpha}(k) \le \frac{4n\left(n+\frac{\alpha+1}{2}\right)}{\alpha^2+10\alpha+8}.$$

Now we obtain from (4.1)

$$\sum_{i=1}^{n} a_{k,i} \le \frac{n}{\alpha+1} + \frac{2\left(n + \frac{\alpha+1}{2}\right)^2}{(\alpha+1)(\alpha-2)} \max_{y \in [0,1]} \varphi_{\alpha}(y) \max_{1 \le k \le n} \psi_{\alpha}(k)$$

$$\le \frac{4}{\alpha^2 + 10\alpha + 8} n \left(n + \frac{\alpha+1}{2} + \frac{\alpha^2 + 10\alpha + 8}{4(\alpha+1)}\right)$$

$$< \frac{4}{\alpha^2 + 10\alpha + 8} n \left(n + \frac{\alpha+1}{2} + \frac{\alpha^2 + 10\alpha + 9}{4(\alpha+1)}\right)$$

$$= \frac{4}{\alpha^2 + 10\alpha + 8} n \left(n + 2 + \frac{3(\alpha+1)}{4}\right).$$

The latter bound is also an upper bound for  $\|\mathbf{A}_n\|_{\infty}$ , therefore Proposition 4.1 is proved in the case  $\alpha > 2$ .

The proof of the case  $\alpha=2$  is similar (and somewhat simpler), and therefore is omitted.  $\Box$ 

Remark 4.1. Actually, the above proof works also in the case  $1 \le \alpha < 2$  (with a minor modification, e.g.,  $\varphi_{\alpha}$  has a minimum instead of maximum in (0,1) but appears in (4.1) with a negative factor, etc.), yielding a similar upper bound for  $\|\mathbf{A}_n\|_{\infty}$ , and hence for  $c_n^2(\alpha)$ . However, for small  $\alpha$  the upper bound for  $c_n^2(\alpha)$  implied by the estimation of  $\|\mathbf{A}_n\|_{\infty}$  is worse than the upper bound given in Theorem A, and also than the upper bound obtained through the Frobenius norm of  $\mathbf{A}_n$ .

### 5. The Frobenius Norm of $A_n$

Let us recall that the Frobenius norm  $\|\cdot\|_F$  of a matrix  $\mathbf{B} = (b_{i,j})_{n \times n}$  with real elements is defined by

$$\|\mathbf{B}\|_F^2 = \sum_{i=1}^n \sum_{j=1}^n b_{i,j}^2 = \operatorname{tr}(\mathbf{B}^{\top}\mathbf{B}).$$

Since  $\mathbf{A}_n$  is a symmetric and positive definite matrix, we have

$$\|\mathbf{A}_n\|_F^2 = \operatorname{tr}(\mathbf{A}_n^2) = \mu_1^2 + \mu_2^2 + \dots + \mu_n^2,$$
 (5.1)

where  $0 < \mu_1 < \mu_2 < \dots < \mu_n = \mu_{\max}(\mathbf{A}_n)$  are the eigenvalues of  $\mathbf{A}_n$ , i.e., the zeros of the characteristic polynomial  $P_n(\mu) = \det(\mu \mathbf{E}_n - \mathbf{A}_n)$ ,

$$P_n(\mu) = \mu^n - b_1 \,\mu^{n-1} + b_2 \,\mu^{n-2} - b_3 \,\mu^{n-3} + \dots + (-1)^n b_n \,.$$

In [3] we evaluated coefficients  $b_i$ ,  $1 \le i \le 3$ , as a part of the proof of Theorem A. These coefficients are given below:

$$b_1 = \operatorname{tr}(\mathbf{A}_n) = \frac{n(n+1)}{2(\alpha+1)},$$

$$b_2 = \frac{(n-1)n(n+1)}{24(\alpha+1)(\alpha+2)(\alpha+3)} \left[ 3(\alpha+2)n + 2(\alpha+6) \right],$$

$$b_3 = (n-2)(n-1)n(n+1)$$

$$\times \frac{\left[ 5(\alpha+2)(\alpha+4)n(n+1) + 8(7\alpha+20)n + 12(\alpha+20) \right]}{240(\alpha+1)(\alpha+2)(\alpha+3)(\alpha+4)(\alpha+5)}.$$

Estimates for  $c_n^2(\alpha) = \mu_{\max}(\mathbf{A}_n)$  are also possible in terms of solely the first two coefficients,  $b_1$  and  $b_2$ . Indeed, since  $\operatorname{tr}(\mathbf{A}_n) = b_1$  and, by (5.1),  $\|\mathbf{A}_n\|_F^2 = b_1^2 - 2b_2$ , we have

$$b_1 - 2\frac{b_2}{b_1} = \frac{\|\mathbf{A}_n\|_F^2}{\operatorname{tr}(\mathbf{A}_n)} \le \mu_{\max}(\mathbf{A}_n) \le \|\mathbf{A}_n\|_F = (b_1^2 - 2b_2)^{1/2}.$$

Replacing  $b_1$  and  $b_2$  in the first and the last expression, we obtain the estimates

$$c_n^4(\alpha) \le \frac{n(n+1)}{2(\alpha+1)^2(\alpha+3)} \left( n^2 + \frac{2\alpha^2 + 5\alpha + 6}{3(\alpha+2)} n + \frac{(\alpha+1)(\alpha+6)}{3(\alpha+2)} \right), \quad (5.2)$$

$$c_n^2(\alpha) \ge \frac{n^2}{(\alpha+1)(\alpha+3)} + \frac{(2\alpha^2 + 5\alpha + 6)n}{3(\alpha+1)(\alpha+2)(\alpha+3)} + \frac{\alpha+6}{3(\alpha+2)(\alpha+3)}, \quad (5.3)$$

the second being nothing but the lower estimate (1.2) of Dörfler.

Slightly weaker but simpler estimates can be obtained on the basis of (5.2) and (5.3).

**Proposition 5.1.** For all  $n \geq 3$ , the best Markov constant  $c_n(\alpha)$  satisfies the inequalities

$$c_n^2(\alpha) \le \frac{(n+1)\sqrt{n\left(n + \frac{2(\alpha+1)}{3}\right)}}{(\alpha+1)\sqrt{2(\alpha+3)}}, \qquad \alpha > -1,$$

$$(5.4)$$

$$c_n^2(\alpha) \ge \begin{cases} \frac{n(n + \frac{7}{8})}{(\alpha + 1)(\alpha + 3)}, & \alpha \in (-1, 0), \\ \frac{n(n + 1)}{(\alpha + 1)(\alpha + 3)}, & \alpha \in [0, 1], \\ \frac{n(n + \frac{2\alpha + 1}{3})}{(\alpha + 1)(\alpha + 3)}, & \alpha \ge 1. \end{cases}$$
(5.5)

*Proof.* Inequality (5.4) follows from (5.2) and the inequality

$$n^{2} + \frac{2\alpha^{2} + 5\alpha + 6}{3(\alpha + 2)}n + \frac{(\alpha + 1)(\alpha + 6)}{3(\alpha + 2)} \le (n + 1)\left(n + \frac{2\alpha + 1}{3}\right).$$

The latter simplifies to the inequality

$$\frac{(\alpha+1)(4n+\alpha-2)}{3(\alpha+2)} \ge 0$$

which is obviously true.

From (5.3) we have

$$c_n^2(\alpha) \ge \frac{n\left(n + \frac{2\alpha^2 + 5\alpha + 6}{3(\alpha + 2)}\right)}{(\alpha + 1)(\alpha + 3)} = \frac{n\left(n + \frac{2\alpha + 1}{3} + \frac{4}{3(\alpha + 2)}\right)}{(\alpha + 1)(\alpha + 3)},$$

whence the case  $\alpha \geq 1$  in (5.5) readily follows. For the proof of the cases  $\alpha \in (-1,0)$  and  $\alpha \in [0,1]$ , we observe that  $g(\alpha) = \frac{2\alpha^2 + 5\alpha + 6}{3(\alpha + 2)}$  has a unique local extremum in (-1,1], a minimum, which is attained at  $\alpha_* = \sqrt{2} - 2 \in (-1,0)$ . Hence,  $g(\alpha) \geq g(\alpha_*) = \frac{4\sqrt{2}}{3} - 1 > \frac{7}{8}$  for  $\alpha \in (-1,0)$ , and  $g(\alpha) \geq g(0) = 1$  for  $\alpha \in [0,1]$ .

Remark 5.1. Estimates (5.2) and (5.3) and their consequences (5.4) and (5.5) are inferior to the estimates in Theorem A in the sense that they imply weaker estimates for the asymptotic Markov constant  $c(\alpha)$ . It can be also shown that the upper estimate in Theorem A is superior to (5.4) for every  $\alpha > -1$  and  $n \geq 3$ . On the other hand, for small n Dörfler's lower estimate (5.3) and the lower estimates in Proposition 5.1 are superior to the lower estimate in Theorem A.

### 6. Proof of Corollaries 1.1–1.3

*Proof of Corollary 1.1.* The right-hand side inequality follows from Theorem 1.1: for  $\alpha \geq 2$  we have

$$c_n^2(\alpha) \leq \frac{4n\left(n+2+\frac{3(\alpha+1)}{4}\right)}{\alpha^2+10\alpha+8} < \frac{4n(n+\alpha+3)}{\alpha^2+9\alpha+8} = \frac{4n(n+\alpha+3)}{(\alpha+1)(\alpha+8)}.$$

For the left-hand side inequality we make use of estimate (5.5), the case  $\alpha \geq 1$ . For  $n \geq 3$  we have

$$c_n^2(\alpha) \ge \frac{n\left(n + \frac{2\alpha + 1}{3}\right)}{(\alpha + 1)(\alpha + 3)} > \frac{2n\left(n + \alpha + \frac{1}{2}\right)}{3(\alpha + 1)(\alpha + 3)}$$
$$\ge \frac{2n\left(n + \alpha + \frac{1}{2} + 5\right)}{3(\alpha + 1)(\alpha + 8)} > \frac{2n(n + \alpha + 3)}{3(\alpha + 1)(\alpha + 8)},$$

where for the first inequality in the second line we have used that  $f(x) = \frac{x+a}{x+b}$  is a decreasing function in  $(0, \infty)$  when a > b > 0. This proves the left-hand side inequality in Corollary 1.1.

Proof of Corollary 1.2. (i) From (5.3) we deduce that

$$\lim_{\alpha \to -1} (\alpha+1)c_n^2(\alpha) \ge \frac{n(n+1)}{2},$$

while from the upper estimate in Theorem A we obtain

$$\lim_{\alpha \to -1} (\alpha + 1)c_n^2(\alpha) \le \frac{n(n+1)}{2}$$

(notice that the same conclusion follows from (5.4)).

(ii) The right-hand side inequality follows from Theorem 1.1, and the left-hand side inequality follows from (5.5).

Proof of Corollary 1.3. The lower estimate is a consequence from Theorem A, while the upper estimates follow from Theorem A and Theorem 1.1, respectively.  $\Box$ 

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