ASYMPTOTIC EXPANSIONS AND TWO-SIDED BOUNDS
IN RANDOMIZED CENTRAL LIMIT THEOREMS

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Abstract. Lower and upper bounds are explored for the uniform (Kolmogorov) and $L^2$-
distances between the distributions of weighted sums of dependent summands and the normal
law. The results are illustrated for several classes of random variables whose joint distribu-
tions are supported on Euclidean spheres. We also survey several results on improved rates
of normal approximation in randomized central limit theorems.

1. Introduction

A random vector $X = (X_1, \ldots, X_n)$ in $\mathbb{R}^n$ $(n \geq 2)$ defined on the probability space $(\Omega, \mathfrak{F}, \mathbb{P})$
is called isotropic, if
\[ \mathbb{E}X_i X_j = \delta_{ij} \quad \text{for all } i, j \leq n \]
where $\delta_{ij}$ is the Kronecker symbol. Equivalently, all weighted sums
\[ S_\theta = \theta_1 X_1 + \cdots + \theta_n X_n, \quad \theta = (\theta_1, \ldots, \theta_n), \quad \theta_1^2 + \cdots + \theta_n^2 = 1, \]
with coefficients from the unit sphere $S^{n-1}$ in $\mathbb{R}^n$ have a second moment $\mathbb{E}S_\theta^2 = 1$. In this
case, provided that the Euclidean norm $|X|$ is almost constant, and if $n$ is large, a theorem
due to Sudakov [29] asserts that the distribution functions
\[ F_\theta(x) = \mathbb{P}\{S_\theta \leq x\}, \quad x \in \mathbb{R}, \]
are well approximated for most of $\theta \in S^{n-1}$ by the standard normal distribution function
\[ \Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} e^{-y^2/2} dy. \]
Here, “most” should refer to the normalized Lebesgue measure $s_{n-1}$ on the sphere. This
property may be quantified, for example, in terms of the Kolmogorov distance
\[ \rho(F_\theta, \Phi) = \sup_x |F_\theta(x) - \Phi(x)|. \]

Being rather universal (since no independence of the components $X_k$ is required), ran-
domized central limit theorems of such type have received considerable interest in the recent
years. For the history, bibliography, and interesting connections with other concentration
problems we refer an interested reader to [8, 9] and [13]. Let us mention one general upper
bound
\[ \mathbb{E}_\theta \rho(F_\theta, \Phi) \leq c (1 + \sigma_4) \frac{\log n}{\sqrt{n}}, \quad (1.1) \]

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which holds true with an absolute constant $c > 0$ for any isotropic random vector $X$ (cf. Theorem 1.2 in [8]). Here and elsewhere, $\mathbb{E}_\theta$ denotes an integral over $S^{n-1}$ with respect to the measure $s_{n-1}$ and the bound involves the variance-type functional

$$
\sigma_4^2 = \sigma_4^2(X) = \frac{1}{n} \text{Var}(|X|^2) \quad (\sigma_4 \geq 0).
$$

Modulo a logarithmic factor, the bound (1.1) exhibits a standard rate of normal approximation for $F_\theta$, in analogy with the classical case of independent identically distributed (iid) summands with equal coefficients. It turns out, however, that in the model with arbitrary $\theta \in S^{n-1}$ and independent components $X_k$, the standard rate for $\rho(F_\theta, \Phi)$ is dramatically improved to the order $1/n$ on average and actually for most of $\theta$. Motivated by the seminal paper of Klartag and Sodin [21], this interesting phenomenon was recently studied in [9], [10] for dependent data under certain correlation-type conditions. The last chapters of this paper provide a short account of these improved rates of normal approximation.

One of the main aims of this work is to develop lower bounds with a similar standard rate (modulo logarithmic factors) and to illustrate them with a number of examples of random variables $X_k$ often appearing in Functional Analysis. These results rely on a careful examination of the closely related $L^2$-distance

$$
\omega(F_\theta, \Phi) = \left( \int_{-\infty}^{\infty} (F_\theta(x) - \Phi(x))^2 \, dx \right)^{1/2}.
$$

Similarly to (1.1), it can be shown that for the class of isotropic random vectors the inequality

$$
\mathbb{E}_\theta \omega^2(F_\theta, \Phi) \leq c \left( 1 + \sigma_4^2 \right) \frac{1}{n}
$$

(1.2)

holds without an unnecessary logarithmic term. However, in order to explore the real behavior of the average $L^2$-distance, some other characteristics of the distribution of $X$ are required. For example, assuming that the distribution is supported on the sphere $\sqrt{n} S^{n-1}$, the $L^2$-distance admits an asymptotic expansion in terms of the moment functionals (normalized $L^p$-norms)

$$
m_p = m_p(X) = \frac{1}{\sqrt{n}} \left( \mathbb{E}(X_i Y)^p \right)^{1/p} = \frac{1}{\sqrt{n}} \left( \sum \mathbb{E}(X_{i_1} \ldots X_{i_p})^2 \right)^{1/p}.
$$

Here, $Y$ is an independent copy of $X$, and the summation is performed over all indices $1 \leq i_1, \ldots, i_p \leq n$. The second representation shows that these functionals are non-negative for any integer $p \geq 1$. Note that $m_1 = 0$ if $X$ has mean zero, and $m_2 = 1$ if $X$ is isotropic, and that $m_p = 0$ with odd $p$ when the distribution of $X$ is symmetric about the origin. The following expansion involves the moments $m_p$ up to order 4.

**Theorem 1.1.** Let $X$ be an isotropic random vector in $\mathbb{R}^n$ with mean zero and such that $|X|^2 = n$ a.s. We have

$$
\mathbb{E}_\theta \omega^2(F_\theta, \Phi) = \frac{c_1}{n^{3/2}} m_3^3 + \frac{c_2}{n^2} m_4^4 + O\left( \frac{1}{n^2} \right) \quad (1.3)
$$

with $c_1 = \frac{1}{16 \sqrt{\pi}}$ and $0.01 < c_2 < 3$. Similarly, with some absolute constants $c_3, c_4 > 0$,

$$
\mathbb{E}_\theta \rho^2(F_\theta, \Phi) \leq \frac{c_3 \log n}{n^{3/2}} m_3^3 + \frac{c_4 (\log n)^2}{n^2} m_4^4. \quad (1.4)
$$
In the general isotropic case with bounded \( \sigma_4 \) (thus without the support assumption), the average \( L^2 \)-distance is described by a more complicated formula

\[
\mathbb{E}_\theta \omega^2(F_\theta, \Phi) = \frac{1}{\sqrt{2\pi n}} \left( 1 + \frac{1}{8n} \right) \mathbb{E}\sqrt{|X|^2 + |Y|^2} - \frac{1}{\sqrt{2\pi n}} \left( 1 + \frac{1}{4n} \right) \mathbb{E}|X - Y| + O\left( \frac{1 + \sigma_4^2}{n^\frac{1}{2}} \right),
\]

which holds whenever \( \mathbb{E}|X|^2 = n \).

Since \( m_4 \geq 1 \), the error term in (1.3) is dominated by the second term involving \( m_4 \).

Using the pointwise bound \( |\langle X, Y \rangle| \leq n \) together with the isotropy assumption, we have \( \mathbb{E}\langle X, Y \rangle^3 \leq n^2 \) and \( \mathbb{E}\langle X, Y \rangle^4 \leq n^3 \). Therefore, the inequalities (1.3)-(1.4) yield with some absolute constant \( c > 0 \)

\[
\mathbb{E}_\theta \omega^2(F_\theta, \Phi) \leq c \frac{n}{n^\frac{1}{2}}, \quad \mathbb{E}_\theta \rho^2(F_\theta, \Phi) \leq \frac{c (\log n)^2}{n^\frac{1}{2}},
\]

thus recovering the upper bounds (1.1)-(1.2) for this particular case (since \( \sigma_4 = 0 \)). On the other hand, for a large variety of examples, such bounds turn out to be optimal and may be reversed modulo a logarithmic factor (for large \( n \)). To see this, one may use the following lower bound which will be derived from a slightly modified variant of (1.5).

**Theorem 1.2.** Let \( X \) be a random vector in \( \mathbb{R}^n \) satisfying \( \mathbb{E}|X|^2 = n \), and let \( Y \) be its independent copy. For some absolute constants \( c_1, c_2 > 0 \), we have

\[
\mathbb{E}_\theta \omega^2(F_\theta, \Phi) \geq c_1 \mathbb{P}\left\{ |X - Y| \leq \frac{1}{2} \sqrt{n} \right\} - c_2 \frac{1 + \sigma_4^4}{n^2}. \tag{1.7}
\]

Thus, if the probability in (1.7) is of order at least \( 1/n \), and \( \sigma_4 \) is bounded, the right-hand side of this bound will be of the same order. If, for example, \( |X| = \sqrt{n} \) a.s., we then obtain that \( \mathbb{E}_\theta \omega^2(F_\theta, \Phi) \sim 1/n \).

In order to derive a similar conclusion for the Kolmogorov distance, one may refer to the next statement.

**Theorem 1.3.** Let \( X \) be an isotropic random vector in \( \mathbb{R}^n \) such that \( |X| \leq b \sqrt{n} \) a.s. Suppose that we have a lower bound at the standard rate

\[
\mathbb{E}_\theta \omega^2(F_\theta, \Phi) \geq \frac{D}{n}
\]

with some \( D > 0 \). Then with some absolute constants \( c_0, c_1 > 0 \)

\[
\mathbb{E}_\theta \rho(F_\theta, F) \geq \frac{c_0}{(1 + \sigma_4^2)^3 b^2} \frac{D^2}{(\log n)^4 \sqrt{n}} - \frac{c_1 (1 + \sigma_4^2)}{n^\frac{1}{2}}.
\]

These estimates may be employed to arrive at two-sided bounds of the form

\[
\frac{c_0}{n} \leq \mathbb{E}_\theta \omega^2(F_\theta, \Phi) \leq \frac{c_1}{n}, \quad \frac{c_0}{(\log n)^4 \sqrt{n}} \leq \mathbb{E}_\theta \rho(F_\theta, \Phi) \leq \frac{c_1 \log n}{\sqrt{n}},
\]

with some absolute constants \( c_0 > 0 \) and \( c_1 > 0 \). Examples where both inequalities in (1.8) are fulfilled include the following uniformly bounded orthonormal systems in \( L^2(\Omega, \mathcal{F}, \mathbb{P}) \):
(i) The trigonometric system $X = (X_1, \ldots, X_n)$ with components

\[ X_{2k-1}(t) = \sqrt{2} \cos(kt), \]
\[ X_{2k}(t) = \sqrt{2} \sin(kt) \quad (-\pi < t < \pi, \ k = 1, \ldots, n/2, \ n \text{ even}) \]

on the interval $\Omega = (-\pi, \pi)$ equipped with the normalized Lebesgue measure $P$.

(ii) The cosine trigonometric system $X = (X_1, \ldots, X_n)$ with

\[ X_k(t) = \sqrt{2} \cos(kt) \quad (0 < t < \pi) \]

on the interval $\Omega = (0, \pi)$ equipped with the normalized Lebesgue measure $P$.

(iii) The normalized Chebyshev polynomials $X_1, \ldots, X_n$ defined by

\[ X_k(t) = \sqrt{2} \cos\left(\frac{\arccos t}{2}\right) = \sqrt{2} \left[ t^n - \left(\frac{n}{2}\right) t^{n-2} (1 - t^2) + \left(\frac{n}{4}\right) t^{n-4} (1 - t^2)^2 - \ldots \right] \]

on the interval $\Omega = (-1, 1)$ equipped with the probability measure $dP(t) = \frac{1}{\pi \sqrt{1-t^2}} dt$, $|t| < 1$.

(iv) The systems of functions of the form

\[ X_k(t, s) = \Psi(kt + s), \quad k = 1, \ldots, n \quad (0 < t, s < 1) \]

on the square $\Omega = (0,1) \times (0,1)$ equipped with the Lebesgue measure $P$. In this case, (1.8) holds true for any 1-periodic Lipschitz function $\Psi$ on the real line such that \( \int_0^1 \Psi(x) dx = 0 \) and \( \int_0^1 \Psi(x)^2 dx = 1 \) with constants $c_0$ and $c_1$ depending on $\Psi$ only.

(v) The Walsh system

\[ X = \{X_\tau\}_{\tau \neq \emptyset}, \quad \tau \subset \{1, \ldots, d\}, \]

of dimension $n = 2^d - 1$ on the discrete cube $\Omega = \{-1, 1\}^d$ (the ordering of the components does not play any role). Here, $P$ denotes the normalized counting measure, and

\[ X_\tau(t) = \prod_{k \in \tau} t_k \quad \text{for} \ t = (t_1, \ldots, t_d) \in \Omega. \]

(vi) Random vectors $X$ with associated empirical distribution functions $F_\theta$ based on the “observations” $X_k = \sqrt{n} \theta_k$ ($1 \leq k \leq n$).

The paper is organized as follows. We start in Section 2 with a review of several results on the so-called typical distributions $F$ which serve as main approximations for $F_\theta$ (in general, they do not need to be normal, or even nearly normal). Sections 3-7 deal with the $L^2$-distances $\omega(F_\theta, F)$ only, while Sections 8-12 are mostly focused on the Kolmogorov distances $\rho(F_\theta, F)$. In Section 13, the examples described in items (i)-(vi) illustrate the applicability of Theorems 1.1-1.3, thus with a standard rate of normal approximation. In Section 14 we consider lacunary trigonometric systems and show that the typical rate is improved to the order $1/n$. Similar improved rates are also reviewed in the last section in presence of certain correlation-type conditions. Thus an outline of all sections reads as:

1. Introduction
2. Typical distributions
3. Upper bound for the $L^2$-distance at standard rate
4. General approximations for the $L^2$-distance with error of order at most $1/n$
5. Proof of Theorem 1.1 for the $L^2$-distance
6. General lower bounds for the $L^2$-distance. Proof of Theorem 1.2
7. Lipschitz systems
8. Berry-Esseen-type bounds
9. Quantitative forms of Sudakov’s theorem for the Kolmogorov distance
10. Proof of Theorem 1.1 for the Kolmogorov Distance
11. Relations between $L^1$, $L^2$ and Kolmogorov distances
12. Lower bounds. Proof of Theorem 1.3
13. Functional examples
14. The Walsh system; Empirical measures
15. Improved rates for lacunary systems
16. Improved rates for independent and log-concave summands
17. Improved rates under correlation-type conditions

As usual, the Euclidean space $\mathbb{R}^n$ is endowed with the canonical norm $|\cdot|$ and the inner product $\langle \cdot, \cdot \rangle$. In the sequel, we denote by $E_\theta$ an integral over $S^{n-1}$ with respect to the measure $s_{n-1}$. By $c, c_1, c_2, \ldots$, we denote positive absolute constants which may vary from place to place (if not stated explicitly that $c$ depends on some parameter). Similarly $C$ will denote a quantity bounded by an absolute constant. Throughout, we assume that $X$ is a given random vector in $\mathbb{R}^n$ ($n \geq 2$) and $Y$ is its independent copy.

2. Typical Distributions

In the sequel, we denote by

$$F(x) = E_\theta F_\theta(x) = E_\theta P\{S_\theta \leq x\}, \quad x \in \mathbb{R},$$

the mean distribution function of the weighted sums $S_\theta = \langle X, \theta \rangle$ with respect to the uniform measure $s_{n-1}$. It is also called a typical distribution function using the terminology of [29]. Indeed, according to Sudakov’s theorem, if $X$ is isotropic, then most of $F_\theta$ are concentrated about $\Phi$ in a weak sense (cf. [1], [3], [8] for quantitative statements).

However, whether or not $F$ itself is close to the normal distribution function $\Phi$ is determined by the concentration properties of the distribution of $|X|$. Note that, due to the rotational invariance of $s_{n-1}$, the typical distribution can be described as the distribution of the product $\theta_1 |X|$, assuming that $\theta = (\theta_1, \ldots, \theta_n)$ is a random vector which is independent of $X$ and has distribution $s_{n-1}$. In this product, $\theta_1 \sqrt{n}$ is almost standard normal, so that $F$ is almost standard normal, if and only if $\frac{1}{\sqrt{n}} |X|$ is almost 1 (like in the weak law of large numbers). This assertion can be quantified in terms of the weighted total variation distance by virtue of the following upper bound derived in [7].

**Proposition 2.1.** If $E |X|^2 = n$ (in particular, when $X$ is isotropic), we have

$$\int_{-\infty}^{\infty} (1 + x^2) |F(dx) - \Phi(dx)| \leq \frac{c}{n} \left(1 + \text{Var}(|X|)\right).$$

In particular, this gives a non-uniform bound for the normal approximation, namely

$$|F(x) - \Phi(x)| \leq \frac{c}{n} \left(1 + \text{Var}(|X|)\right), \quad x \in \mathbb{R}. \quad (2.1)$$

In these bounds we shall rely on the following monotone functionals (of $p$)

$$\sigma_{2p} = \sqrt{n} \left(E \left|\frac{|X|^2}{n} - 1\right|^p\right)^{1/p}, \quad p \geq 1, \quad (2.2)$$
where the particular cases $p = 1$ and $p = 2$ will be most important. If $\mathbb{E}|X|^2 = n$, we thus deal with a more tractable quantity

$$\sigma_4^2 = \frac{1}{n} \text{Var}(|X|^2).$$

Using an elementary inequality $\text{Var}(\xi) \mathbb{E} \xi^2 \leq \text{Var}(\xi^2)$ (which is true for any random random variable $\xi \geq 0$), we have $\text{Var}(|X|) \leq \sigma_4^2$. Another similar relation

$$\frac{1}{4} \sigma_2^2 \leq \text{Var}(|X|) \leq \sqrt{n} \sigma_2$$

can be found in [8]. From (2.1), we therefore obtain the following bounds for the normal approximation in all $L^p$-norms

$$\|F - \Phi\|_p = \left( \int_{-\infty}^{\infty} |F(x) - \Phi(x)|^p \, dx \right)^{1/p},$$

including the limit case

$$\|F - \Phi\|_\infty = \rho(F, \Phi) = \sup_x |F(x) - \Phi(x)|.$$

**Corollary 2.2.** If $\mathbb{E}|X|^2 = n$, then, for all $p \geq 1$,

$$\|F - \Phi\|_p \leq c \frac{1 + \sigma_2}{\sqrt{n}}, \quad \|F - \Phi\|_p \leq c \frac{1 + \sigma_4^2}{n}. \tag{2.3}$$

Note that the characteristic function associated to $F$ is given by

$$f(t) = \mathbb{E}_{\theta} \mathbb{E} e^{it(X,\theta)} = \mathbb{E}_{\theta} \mathbb{E} e^{it|X|} \theta_1 = \mathbb{E} J_n(t|X|), \quad t \in \mathbb{R}, \tag{2.4}$$

where $J_n$ denotes the characteristic function of the first coordinate $\theta_1$ of $\theta$ under $s_{n-1}$. Hence, by the Plancherel theorem,

$$\omega^2(F, \Phi) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \left( \mathbb{E} J_n(t|X|) - e^{-t^2/2} \right)^2 \frac{dt}{t^2}. \tag{2.5}$$

For $p = 2$, the relations in (2.3) can also be derived by means of (2.5) and by virtue of the following Edgeworth-type approximations derived in [8] and [10].

**Lemma 2.3.** For all $t \in \mathbb{R}$,

$$|J_n(t\sqrt{n}) - e^{-t^2/2}| \leq \frac{c}{n} \min\{1, t^2\}. \tag{2.6}$$

Moreover,

$$|J_n(t\sqrt{n}) - \left(1 - \frac{t^4}{4n}\right) e^{-t^2/2}| \leq \frac{c}{n^2} \min\{1, t^4\}. \tag{2.7}$$

The functions $J_n$ have a subgaussian (although oscillatory) decay on a long interval of the real line. In particular, as was shown in [8],

$$|J_n(t\sqrt{n})| \leq 5 e^{-t^2/2} + 4 e^{-n/12}, \quad t \in \mathbb{R}. \tag{2.8}$$

This bound can be used for the estimation of the characteristic function of the typical distribution, by involving the variance-type functionals $\sigma_{2p}$. 
Lemma 2.4. The characteristic function of the typical distribution satisfies, for all $t \in \mathbb{R}$,

$$c_p |f(t)| \leq e^{-t^2/4} + \frac{1 + \sigma_{2p}^p}{n^{p/2}}$$

with constants $c_p > 0$ depending on $p \geq 1$ only. Consequently, for all $T > 0$,

$$\frac{c_p}{T} \int_0^T |f(t)| \, dt \leq \frac{1}{T} + \frac{1 + \sigma_{2p}^p}{n^{p/2}}.$$

Proof. One may split the expectation in (2.4) to the event $A = \{|X|^2 \leq \lambda n\}$ and its complement $B = \{|X|^2 > \lambda n\}$, $0 < \lambda < 1$. By (2.8),

$$\mathbb{E}|J_n(t|X)|_1 \leq \mathbb{E}(5e^{-t^2|X|^2/2n} + 4e^{-n/12})_1B \leq 5e^{-\lambda t^2/2} + 4e^{-n/12}.$$

On the other hand, recalling the definition (2.2), we have

$$\mathbb{P}(A) = \mathbb{P}\{n - |X|^2 \geq (1 - \lambda)n\} \leq \frac{\mathbb{E}|n - |X|^2|^p}{((1 - \lambda)n)^p} = \frac{\sigma_{2p}^p}{(1 - \lambda)^p n^{p/2}}. \quad (2.9)$$

Choosing $\lambda = \frac{1}{2}$, and since $|J_n(s)| \leq 1$ for all $s \in \mathbb{R}$, we get

$$\mathbb{E}|J_n(t|X)|_A \leq (2\sigma_{2p})^p n^{-p/2},$$

thus implying that

$$|f(t)| \leq 5e^{-t^2/4} + 4e^{-n/12} + (2\sigma_{2p})^p n^{-p/2}.$$

This readily yields the desired pointwise and integral bounds of the lemma. \quad \square

If $|X| = \sqrt{n}$ a.s., the typical distribution $F$ is just the distribution of $\sqrt{n} \theta_1$, the normalized first coordinate of a point on the unit sphere under $s_{n-1}$, whose characteristic function is $J_n(t\sqrt{n})$. In this case, the subgaussian character of $F$ manifests itself in corresponding deviation and moment inequalities such as the following.

Lemma 2.5. For all $p > 0$,

$$\mathbb{E}|\theta_1|^p \leq 2 \left(\frac{p}{n}\right)^{p/2}. \quad (2.10)$$

This inequality can be derived from the well-known bound on the Laplace transform

$$\mathbb{E}e^{t\theta_1} \leq \exp\left\{\frac{t^2}{2(n-1)}\right\}, \quad t \in \mathbb{R}$$

(cf. [23]). Using $|x|^p \leq 2 \left(\frac{p}{n}\right)^p \cosh(x)$ ($x \in \mathbb{R}$), we then get

$$t^p \mathbb{E}|\theta_1|^p \leq 2 \left(\frac{p}{n}\right)^p e^{t^2/2(n-1)}$$

for all $t \geq 0$. The latter can be optimized over $t$, which leads to (2.10), even in a sharper form.

In this connection, let us emphasize that rates for the normal approximation for $F$ that are better than $1/n$ cannot be obtained under the support assumption as above.

Proposition 2.6. For any random vector $X$ in $\mathbb{R}^n$ such that $|X|^2 = n$ a.s., we have

$$\mathbb{E}_\theta \rho(F, \Phi) \geq \frac{c}{n}.$$
Proof. One may apply the following lower bound
\[
\rho(F, \Phi) \geq \frac{1}{3T} \left| \int_0^T (f(t) - e^{-t^2/2}) \left( 1 - \frac{t}{T} \right) \, dt \right|, \tag{2.11}
\]
which holds for any \( T > 0 \) (cf. [4]). Since \(|X|^2 = n\) a.s., we have \( f(t) = J_n(t\sqrt{n})\). Choosing \( T = 1 \) and applying (2.7), it follows from (2.11) that \( \rho(F, \Phi) \geq \frac{c}{n} \) for all \( n \geq n_0 \) where \( n_0 \) is determined by \( c \) only. But, a similar bound also holds for \( n < n_0 \) since \( F \) is supported on the interval \([-\sqrt{n}, \sqrt{n}]\).

3. Upper Bound for the \( L^2 \)-distance at Standard Rate

Like in the problem of normal approximation for the typical distribution function \( F = \mathbb{E}_\theta F_\theta \), the closeness of distribution functions \( F_\theta \) of the weighted sums \( S_\theta = \langle X, \theta \rangle \) (\( \theta \in S_n \)) to \( F \) in the metric \( \omega \) can also be explored in terms of the associated characteristic functions (the Fourier-Stieltjes transforms)
\[
f_\theta(t) = \mathbb{E} e^{it\langle X, \theta \rangle} = \int_{-\infty}^{\infty} e^{itx} \, dF_\theta(x), \quad t \in \mathbb{R}. \tag{3.1}
\]
Again, let us start with the identity
\[
\omega^2(F_\theta, F) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \frac{|f_\theta(t) - f(t)|^2}{t^2} \, dt. \tag{3.2}
\]
Here, the mean value of the numerator represents the variance \( \mathbb{E}_\theta |f_\theta(t)|^2 \) with respect to \( s_{n-1} \). Moreover, using an independent copy \( Y \) of \( X \), we have
\[
\mathbb{E}_\theta |f_\theta(t)|^2 = \mathbb{E}_\theta \mathbb{E} e^{it\langle X-Y, \theta \rangle} = \mathbb{E} J_n(t|X-Y|). \tag{3.3}
\]
Hence, the Plancherel formula (3.2) together with (2.4) yields
\[
\mathbb{E}_\theta \omega^2(F_\theta, F) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \left( \mathbb{E} J_n(t|X-Y|) - (\mathbb{E} J_n(t|X|))^2 \right) \frac{dt}{t^2}. \tag{3.4}
\]

In this section our aim is to show that the above expression is of order at most \( O(1/n) \) provided that the mean \( a = \mathbb{E} X \), \( m_2 = m_2(X) \) and \( \sigma_4^2 = \sigma_4^2(X) \) are of order 1. The next statement contains the upper bound (1.2) as a partial case.

**Proposition 3.1.** Given a random vector \( X \) in \( \mathbb{R}^n \) with \( \mathbb{E} X = a \) and \( \mathbb{E} |X|^2 = n \), we have
\[
\mathbb{E}_\theta \omega^2(F_\theta, F) \leq \frac{cA}{n} \tag{3.5}
\]
with \( A = 1 + |a|^2 + m_2^2 + \sigma_4^2 \). A similar inequality continues to hold with the normal distribution function \( \Phi \) in place of \( F \).

If \( X \) is isotropic, then \( m_2 = 1 \), while \( |a| \leq 1 \) (by Bessel’s inequality). Hence, both characteristics \( m_2 \) and \( a \) may be removed from the parameter \( A \) in this case. However, in the general case, it may happen that \( m_2 \) and \( \sigma_4 \) are bounded, while \( |a| \) is large. The example in Remark 3.2 shows that this parameter can not be removed.
\textbf{Proof.} Note that, for any $\eta > 0$,

$$
\int_{-\infty}^{\infty} \min \left\{ 1, \frac{t^2 \eta^2}{n} \right\} \, dt = 4\eta, \tag{3.6}
$$

Hence, in the formula (3.4), the expectation $\mathbb{E}J_n(t|X - Y|)$ can be replaced using the normal approximation (2.6) at the expense of an error not exceeding $c/n$.

Similarly, by (2.6) and (3.6),

$$
\int_{-\infty}^{\infty} \left| \mathbb{E}J_n(t|X|)^2 - (\mathbb{E}e^{-t^2|X|^2/2n})^2 \right| \frac{dt}{t^2} \leq 2 \mathbb{E} \int_{-\infty}^{\infty} \left| J_n(t|X|) - e^{-t^2|X|^2/2n} \right| \frac{dt}{t^2} \leq \frac{2c}{n} \int_{-\infty}^{\infty} \min \left\{ 1, \frac{t^2 |X|^2}{n} \right\} \frac{dt}{t^2} = \frac{8c}{n} \mathbb{E} \frac{|X|}{\sqrt{n}} \leq \frac{8c}{n}.
$$

Hence, using these bounds in (3.4), we arrive at the general approximation

$$
\mathbb{E}_{\theta} \omega^2(F_{\theta}, F) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \left( \mathbb{E} e^{-t^2|X - Y|^2/2n} - (\mathbb{E} e^{-t^2|X|^2/2n})^2 \right) \frac{dt}{t^2} + C/n, \tag{3.7}
$$

where we recall that $C$ denotes a quantity bounded by an absolute constant.

Introduce the random variable

$$
\rho^2 = \frac{|X - Y|^2}{2n} \quad (\rho \geq 0).
$$

By Jensen’s inequality, $\mathbb{E} e^{-t^2|X|^2/2n} \geq e^{-t^2/2}$, so that, by (3.7),

$$
\mathbb{E}_{\theta} \omega^2(F_{\theta}, F) \leq \frac{1}{2\pi} \mathbb{E} \int_{-\infty}^{\infty} \frac{e^{-\rho^2 t^2} - e^{-t^2}}{t^2} \, dt + \frac{c}{n}.
$$

The above integral is easily evaluated (by differentiating with respect to the variable “$\rho^2$”), and we arrive at the bound

$$
\mathbb{E}_{\theta} \omega^2(F_{\theta}, F) \leq \frac{1}{\sqrt{\pi}} (1 - \mathbb{E} \rho) + \frac{c}{n}. \tag{3.8}
$$

To further simplify, one may apply an elementary inequality $1 - x \leq \frac{1}{2} (1 - x^2) + (1 - x^2)^2$ $(x \geq 0)$, which gives

$$
\mathbb{E}_{\theta} \omega^2(F_{\theta}, F) \leq \frac{1}{2\sqrt{\pi}} \mathbb{E} (1 - \rho^2) + \frac{1}{\sqrt{\pi}} \mathbb{E} (1 - \rho^2)^2 + \frac{c}{n}.
$$

Since

$$
1 - \rho^2 = \frac{n - |X|^2}{2n} + \frac{n - |Y|^2}{2n} + \frac{\langle X, Y \rangle}{n},
$$

we have

$$
1 - \mathbb{E} \rho^2 = \frac{1}{n} \mathbb{E} \langle X, Y \rangle = \frac{1}{n} |EX|^2 = \frac{1}{n} |a|^2.
$$

In addition,

$$
(1 - \rho^2)^2 \leq 2 \left( \frac{n - |X|^2}{2n} + \frac{n - |Y|^2}{2n} \right)^2 + 2 \frac{\langle X, Y \rangle^2}{n^2}.
$$
which implies
\[ \mathbb{E}(1 - \rho^2)^2 \leq \frac{\text{Var}(|X|^2)}{n^2} + 2 \frac{\mathbb{E}(X,Y)^2}{n^2} = \frac{\sigma_1^2 + 2m_2}{n}. \]

Using this estimate in (3.8), the inequality (3.5) follows immediately.

For the second assertion, it remains to apply Corollary 2.2.

**Remark 3.2.** Let us illustrate the inequality (3.5) in the example where the random vector \( X \) has a normal distribution with a large mean value. Given a standard normal random vector \( Z = (Z_1, \ldots, Z_{n-1}) \) in \( \mathbb{R}^{n-1} \) (which we identify with the space of all points in \( \mathbb{R}^n \) with zero last coordinate), define
\[ X = \alpha Z + \lambda e_n \quad \text{with} \quad 1 \leq \lambda \leq n^{1/4}, \quad \alpha^2(n - 1) + \lambda^2 = n, \]
where \( e_n = (0, \ldots, 0, 1) \) is the last unit vector in the canonical basis of \( \mathbb{R}^n \). Since \( Z \) is orthogonal to \( e_n \), so that \( |X|^2 = \alpha^2|Z|^2 + \lambda^2 \), we have \( \mathbb{E}|X|^2 = n \), and
\[ \sigma_1^2 = \frac{\alpha^4}{n} \text{Var}(|Z|^2) = \frac{2\alpha^4 (n - 1)}{n} = 2 \frac{(n - \lambda^2)^2}{n(n - 1)} < 2. \]

Let \( Z' \) be an independent copy of \( Z \). Then \( Y = \alpha Z' + \lambda e_n \) is an independent copy of \( X \), so that
\[ m_2^2 = \frac{1}{n} \mathbb{E}(X,Y)^2 = \frac{1}{n} (\alpha^4(n - 1) + \lambda^4) < 2. \]

Thus, both \( m_2 \) and \( \sigma_4 \) are bounded, while the mean \( a = \mathbb{E}X = \lambda e_n \) has the Euclidean length \( |a| = \lambda \geq 1 \). Hence, the inequality (3.5) being stated for the normal distribution function in place of \( F \) simplifies to
\[ \mathbb{E}_\theta \omega^2(F_{\theta}, \Phi) \leq \frac{c\lambda^2}{n}. \]

Let us show that this bound may be reversed up to an absolute factor (which would imply that \( |a|^2 \) may not be removed from \( A \)). For any unit vector \( \theta = (\theta_1, \ldots, \theta_n) \), the linear form
\[ S_\theta = \langle X, \theta \rangle = \alpha \theta_1 Z_1 + \cdots + \alpha \theta_{n-1} Z_{n-1} + \lambda \theta_n \]
has a normal distribution on the line with mean \( \mathbb{E}S_\theta = \lambda \theta_n \) and variance \( \text{Var}(S_\theta) = \alpha^2(1 - \theta_n^2) \).
Consider the normal distribution function \( \Phi_{\mu,\sigma^2}(x) = \Phi \left( \frac{x - \mu}{\sigma} \right) \) with parameters \( 0 \leq \mu \leq 1 \) and \( \frac{1}{2} \leq \sigma^2 \leq 1 \) (\( \sigma > 0 \)). If \( x \leq \frac{\mu}{\sqrt{1 - \sigma^2}} \), then \( \frac{x - \mu}{\sigma} \leq x \), and on the interval with these endpoints the standard normal density \( \varphi(y) \) attains minimum at the left endpoint. Hence
\[ |\Phi_{\mu,\sigma^2}(x) - \Phi(x)| = \int_{x-\mu}^{x} \varphi(y) \, dy \geq \left( x - \frac{x - \mu}{\sigma} \right) \varphi \left( \frac{x - \mu}{\sigma} \right), \]
so that
\[ \omega^2(\Phi_{\mu,\sigma^2}, \Phi) \geq \int_{-\infty}^{\frac{\mu}{\sqrt{1 - \sigma^2}}} \left( x - \frac{x - \mu}{\sigma} \right)^2 \varphi \left( \frac{x - \mu}{\sigma} \right)^2 \, dx \]
\[ = \frac{\sigma}{2\pi} \int_{-\infty}^{-\frac{\mu}{\sqrt{1 - \sigma^2}}} (\mu - (1 - \sigma)y)^2 e^{-y^2/2} \, dy \geq \frac{\sigma \mu^2}{2\pi} \int_{-\infty}^{-\frac{\mu}{\sqrt{1 - \sigma^2}}} e^{-y^2/2} \, dy \geq c\mu^2. \]

In our case, since \( \lambda \leq n^{1/4} \) and
\[ \alpha^2 = \frac{n - \lambda^2}{n - 1} \geq \frac{n - \sqrt{n}}{n - 1} \geq 1 - \frac{1}{\sqrt{n}}, \]
we have $|E S_\theta| \leq 1$ and $\text{Var}(S_\theta) \geq \frac{1}{2}$ on the set $\Omega_n = \{ \theta \in S^{n-1} : |\theta_n| < \frac{\log n}{\sqrt{n}} \}$ with $n$ large enough. It then follows that
\[
E_\theta \omega^2(F_\theta, \Phi) \geq c\lambda^2 E\theta_n^2 1_{\{\theta \in \Omega_n\}} \geq \frac{c\lambda^2}{n}.
\]

4. General Approximations for the $L^2$-distance with Error of Order at most $1/n$

We now turn to general representations for the average $L^2$-distance between $F_\theta$ and the typical distribution function $F$ with error of order at most $1/n$.

**Proposition 4.1.** Suppose that $E |X| \leq b\sqrt{n}$ for some $b \geq 0$. Then
\[
E_\theta \omega^2(F_\theta, F) = \frac{1}{\sqrt{2\pi}} E R + \frac{C b}{n^2},
\]
where
\[
R = \frac{(|X|^2 + |Y|^2)^{1/2}}{\sqrt{n}} \left(1 + \frac{1}{4n} \frac{|X|^4 + |Y|^4}{(|X|^2 + |Y|^2)^2}\right) - \frac{|X - Y|}{\sqrt{n}} \left(1 + \frac{1}{4n}\right).
\]

We use the convention that $R = 0$ if $X = Y = 0$. Note that $|R| \leq 3 \frac{|X| + |Y|}{\sqrt{n}}$, so $ER \leq 3b$.

Let us give a simpler expression by involving the functional $\sigma_4^2 = \frac{1}{n} \text{Var}(|X|^2)$ and assuming that $E |X|^2 = n$. Since
\[
\frac{|X|^4 + |Y|^4}{(|X|^2 + |Y|^2)^2} - \frac{1}{2} = \frac{(|X|^2 - |Y|^2)^2}{2 (|X|^2 + |Y|^2)^2},
\]
we may write
\[
R = \frac{1}{8n^{3/2}} \frac{(|X|^2 - |Y|^2)^2}{(|X|^2 + |Y|^2)^{3/2}} + \frac{(|X|^2 + |Y|^2)^{1/2}}{\sqrt{n}} \left(1 + \frac{1}{8n}\right) - \frac{|X - Y|}{\sqrt{n}} \left(1 + \frac{1}{4n}\right).
\]

As we will see, the first term here is actually of order at most $\sigma_4^2/n^2$. As a result, we arrive at the relation (1.5).

**Proposition 4.2.** If $E |X|^2 = n$, then
\[
E_\theta \omega^2(F_\theta, F) = \frac{1}{\sqrt{2\pi}} E R + C \frac{1 + \sigma_4^2}{n^2},
\]
where
\[
R = \frac{(|X|^2 + |Y|^2)^{1/2}}{\sqrt{n}} \left(1 + \frac{1}{8n}\right) - \frac{|X - Y|}{\sqrt{n}} \left(1 + \frac{1}{4n}\right).
\]

**Proof of Proposition 4.1.** Let us return to the Plancherel formula (3.4). To simplify the integrand therein, we apply the inequality (2.7) in Lemma 2.3, by replacing $t^4$ with $t_2^2$ in the remainder term. Using the equality (3.6), the expectation $E J_n(t |X - Y|)$ in the formula (3.4) can be therefore replaced according to (2.7) at the expense of an error not exceeding
\[
\frac{c}{n^2} \int_{-\infty}^{\infty} \min \left\{1, \frac{t^2 |X - Y|^2}{n}\right\} \frac{dt}{t^2} = \frac{4c}{n^2} E \frac{|X - Y|}{\sqrt{n}} \leq \frac{8cb}{n^2}.
\]
Hence, with

As for the main term \((1 - \frac{t^4}{4n}) e^{-t^2/2}\) in (2.7), it is bounded by an absolute constant, which implies that

\[
J_n(t\sqrt{n})J_n(s\sqrt{n}) = \left(1 - \frac{t^4}{4n}\right) \left(1 - \frac{s^4}{4n}\right) e^{-(t^2+s^2)/2} + O(n^{-2}\min\{1, t^2 + s^2\})
\]

Hence

\[
|\mathbb{E}J_n(t|X|)|^2 = \mathbb{E} J_n(t|X|) J_n(t|Y|) = \mathbb{E} \left(1 - \frac{t^4 (|X|^4 + |Y|^4)}{4n^3}\right) e^{-t^2 (|X|^2 + |Y|^2)/2n} + O\left(n^{-2} \min\{1, t^2 (|X|^2 + |Y|^2)/n\}\right).
\]

As before, after integration in (3.4) the latter remainder term will produce a quantity not exceeding a multiple of \(b/n^2\). As a preliminary step, we therefore obtain the representation

\[
\mathbb{E}_\theta \omega^2(F_\theta, F) = \frac{1}{2\pi} I + \frac{Cb}{n^2}
\]

with

\[
I = \mathbb{E} \int_{-\infty}^{\infty} \left(1 - \frac{t^4 |X - Y|^4}{4n^3}\right) e^{-\frac{t^2 |X - Y|^2}{2n}} - \left(1 - \frac{t^4 (|X|^4 + |Y|^4)}{4n^3}\right) e^{-\frac{t^2 (|X|^2 + |Y|^2)}{2n}} \right) dt/4.
\]

To evaluate the integrals of this type, consider the functions

\[
\psi_r(\alpha) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \left(1 - rt^4\right) e^{-\alpha t^2/2} - e^{-t^2/2} \right) dt/4 \quad (\alpha > 0, \ r \in \mathbb{R}).
\]

Clearly,

\[
\psi_r(1) = -\frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} rt^2 e^{-t^2/2} dt = -r
\]

and

\[
\psi'_r(\alpha) = -\frac{1}{2\sqrt{2\pi}} \int_{-\infty}^{\infty} (1 - rt^4) e^{-\alpha t^2/2} dt = -\frac{1}{2\sqrt{\alpha}} \int_{-\infty}^{\infty} \left(1 - \frac{r}{\alpha} s^4\right) e^{-s^2/2} ds = -\frac{1}{2\sqrt{\alpha}} \left(1 - \frac{3r}{\alpha^2}\right).
\]

Hence

\[
\psi_r(\alpha) - \psi_r(1) = \int_1^\alpha \left(1 - \frac{1}{2} z^{-1/2} + \frac{3r}{2} z^{-5/2}\right) dz = (1 + r) - (\alpha^{1/2} + r\alpha^{-3/2}),
\]

and we get

\[
\psi_r(\alpha) = 1 - (\alpha^{1/2} + r\alpha^{-3/2}).
\]

Here, when \(\alpha\) and \(r\) both approach zero subject to the relation \(r = O(\alpha^2)\), we get in the limit \(\psi_0(0) = 1\). From this,

\[
\frac{1}{\sqrt{2\pi}} I = \mathbb{E}(\psi_{r_1}(\alpha_1) - \psi_{r_2}(\alpha_2)) = \mathbb{E}(\alpha_1^{1/2} + r_2\alpha_2^{-3/2}) - \mathbb{E}(\alpha_1^{1/2} + r_1\alpha_1^{-3/2}),
\]
which we need with
\[ \alpha_1 = \frac{|X - Y|^2}{n}, \quad r_1 = \frac{|X - Y|^4}{4n^3}, \]
\[ \alpha_2 = \frac{|X|^2 + |Y|^2}{n}, \quad r_2 = \frac{|X|^4 + |Y|^4}{4n^3}. \]

It follows that
\[ \alpha_2^{1/2} + r_2 \alpha_2^{-3/2} = \left( \frac{|X|^2 + |Y|^2}{n} \right)^{1/2} \left( 1 + \frac{1}{4n} \frac{|X|^4 + |Y|^4}{(|X|^2 + |Y|^2)^2} \right), \]
\[ \alpha_1^{1/2} + r_1 \alpha_1^{-3/2} = \left( \frac{|X - Y|^2}{n} \right)^{1/2} \left( 1 + \frac{1}{4n} \right), \]
with the assumption that both expressions are equal to zero in the case \( X = Y = 0 \). As a result, (4.6) yields the desired representation (4.1) with quantity \( R \) described in (4.2).

In order to modify (4.1)-(4.2) to the form (4.4)-(4.5), first let us verify the following general relation.

**Lemma 4.3.** Let \( \xi \) be a non-negative random variable with finite second moment (not identically zero), and let \( \eta \) be its independent copy. Then
\[
\mathbb{E} \frac{(\xi - \eta)^2}{(\xi + \eta)^{3/2}} 1_{\{\xi + \eta > 0\}} \leq 12 \frac{\operatorname{Var}(\xi)}{(\mathbb{E} \xi)^{3/2}}.
\]

Applying the lemma with \( \xi = |X|^2, \eta = |Y|^2 \) and assuming that \( \mathbb{E} |X|^2 = n \), we get that
\[
\mathbb{E} \frac{|X|^2 - |Y|^2|^2}{(|X|^2 + |Y|^2)^{3/2}} \leq 12 \frac{\operatorname{Var}(|X|^2)}{(\mathbb{E} |X|^2)^{3/2}} = 12 \frac{\operatorname{Var}(|X|^2)}{n^{3/2}} = 12 \frac{\sigma_4^2}{n^{1/2}}.
\]
In view of (4.3), this proves Proposition 4.2.

**Proof of Lemma 4.3.** By homogeneity, we may assume that \( \mathbb{E} \xi = 1 \). In particular, \( \mathbb{E} |\xi - \eta| \leq 2 \). We have
\[
\mathbb{E} \frac{(\xi - \eta)^2}{(\xi + \eta)^{3/2}} 1_{\{\xi + \eta > 1/2\}} \leq 2^{3/2} \mathbb{E} (\xi - \eta)^2 1_{\{\xi + \eta > 1/2\}} \leq 2^{3/2} \mathbb{E} (\xi - \eta)^2 = 4\sqrt{2} \operatorname{Var}(\xi).
\]

Also note that, by Chebyshev’s inequality,
\[
\mathbb{P} \{\xi \leq 1/2\} = \mathbb{P} \{1 - \xi \geq 1/2\} \leq 4 \operatorname{Var}(\xi)^2,
\]
so
\[
\mathbb{P} \{\xi + \eta \leq 1/2\} \leq \mathbb{P} \{\xi \leq 1/2\} \mathbb{P} \{\eta \leq 1/2\} \leq 16 \operatorname{Var}(\xi)^2.
\]
Hence, since \( \frac{\xi - \eta}{\xi + \eta} \leq 1 \) for \( \xi + \eta > 0 \), we have, by Cauchy’s inequality,
\[
\mathbb{E} \frac{(\xi - \eta)^2}{(\xi + \eta)^{3/2}} 1_{\{0 < \xi + \eta \leq 1/2\}} \leq \mathbb{E} \sqrt{|\xi - \eta|} 1_{\{0 < \xi + \eta \leq 1/2\}} \leq \sqrt{\mathbb{E} |\xi - \eta|} \mathbb{P} \{\xi + \eta \leq 1/2\} \leq 4\sqrt{2} \operatorname{Var}(\xi).\]
It remains to combine both inequalities, which yield

\[ E \frac{(\xi - \eta)^2}{(\xi + \eta)^{3/2}} 1_{\{\xi + \eta > 0\}} \leq 8\sqrt{2} \text{Var}(\xi) \leq 12 \text{Var}(\xi). \]

\[ \square \]

5. Proof of Theorem 1.1 for the \(L^2\)-distance

The expression (4.5) may be further simplified in the particular case where the distribution of \(X\) is supported on the sphere \(\sqrt{n} \mathbb{S}^{n-1}\). Introduce the random variable

\[ \xi = \frac{\langle X, Y \rangle}{n}, \]

where \(Y\) is an independent copy of \(X\). Since \(|X - Y|^2 = 2n (1 - \xi)\), Proposition 4.2 yields:

**Corollary 5.1.** If \(|X|^2 = n\) a.s., then

\[ \sqrt{n} \mathbb{E}_\theta \omega^2(F_\theta, F) = \left(1 + \frac{1}{4n}\right) \mathbb{E} \left(1 - (1 - \xi)^{1/2}\right) - \frac{1}{8n} + O\left(\frac{1}{n^2}\right). \quad (5.1) \]

Note that \(|\xi| \leq 1\). Therefore, the relation (5.1) suggests to develop an expansion in powers of \(\varepsilon\) for the function \(w(\varepsilon) = 1 - \sqrt{1 - \varepsilon}\) near zero, which will be needed up to the term \(\varepsilon^4\).

**Lemma 5.2.** For all \(|\varepsilon| \leq 1\),

\[ 1 - \sqrt{1 - \varepsilon} \leq \frac{1}{2} \varepsilon + \frac{1}{8} \varepsilon^2 + \frac{1}{16} \varepsilon^3 + 3\varepsilon^4. \]

In addition,

\[ 1 - \sqrt{1 - \varepsilon} \geq \frac{1}{2} \varepsilon + \frac{1}{8} \varepsilon^2 + \frac{1}{16} \varepsilon^3 + 0.01 \varepsilon^4. \]

**Proof.** By Taylor’s formula for the function \(w(\varepsilon)\) around zero on the half-axis \(\varepsilon < 1\),

\[ 1 - \sqrt{1 - \varepsilon} = \frac{1}{2} \varepsilon + \frac{1}{8} \varepsilon^2 + \frac{1}{16} \varepsilon^3 + \frac{5}{128} \varepsilon^4 + \frac{w^{(5)}(\varepsilon_1)}{120} \varepsilon^5 \]

for some \(\varepsilon_1\) between zero and \(\varepsilon\). Since \(w^{(5)}(\varepsilon) = \frac{105}{32} (1 - \varepsilon)^{-9/2} \geq 0\), we have an upper bound

\[ 1 - \sqrt{1 - \varepsilon} \leq \frac{1}{2} \varepsilon + \frac{1}{8} \varepsilon^2 + \frac{1}{16} \varepsilon^3 + \frac{5}{128} \varepsilon^4, \quad \varepsilon \leq 0. \]

Also, \(w^{(5)}(\varepsilon) \leq \frac{105}{32} \varepsilon^{9/2} < 461\) for \(0 \leq \varepsilon \leq \frac{2}{3}\), so, in this interval

\[ \frac{5}{128} \varepsilon^4 + \frac{w^{(5)}(\varepsilon_1)}{120} \varepsilon^5 \leq 3\varepsilon^4. \]

Thus, in both cases,

\[ 1 - \sqrt{1 - \varepsilon} \leq \frac{1}{2} \varepsilon + \frac{1}{8} \varepsilon^2 + \frac{1}{16} \varepsilon^3 + 3\varepsilon^4, \quad \varepsilon \leq \frac{2}{3}. \]
To treat the remaining values $\frac{2}{3} \leq \varepsilon \leq 1$, it is sufficient to select a positive constant $b$ such that the polynomial

$$Q(\varepsilon) = \frac{1}{2} \varepsilon + \frac{1}{8} \varepsilon^2 + \frac{1}{16} \varepsilon^3 + b \varepsilon^4$$

is greater than or equal to 1 for $\varepsilon \geq \frac{2}{3}$. On this half-axis, $Q(\varepsilon) \geq \frac{11}{27} + b \frac{16}{81} \geq 1$ for $b \geq 3$.

Thus, the upper bound of the lemma is proved.

Now, from Taylor’s formula we also get that

$$1 - \sqrt{1 - \varepsilon} \geq \frac{1}{2} \varepsilon + \frac{1}{8} \varepsilon^2 + \frac{1}{16} \varepsilon^3 + \frac{5}{128} \varepsilon^4, \quad \varepsilon \geq 0.$$

In addition, if $-1 \leq \varepsilon \leq 0$, then $w^{(5)}(\varepsilon) \leq \frac{105}{32}$, so

$$1 - \sqrt{1 - \varepsilon} = \frac{1}{2} \varepsilon + \frac{1}{8} \varepsilon^2 + \frac{1}{16} \varepsilon^3 + \frac{5}{128} \varepsilon^4 \left(1 + \frac{w^{(5)}(\varepsilon)}{120} \varepsilon\right)$$

$$\geq \frac{1}{2} \varepsilon + \frac{1}{8} \varepsilon^2 + \frac{1}{16} \varepsilon^3 + \frac{5}{128} \varepsilon^4 \left(1 - \frac{105}{120}\right)$$

$$\geq \frac{1}{2} \varepsilon + \frac{1}{8} \varepsilon^2 + \frac{1}{16} \varepsilon^3 + 0.01 \varepsilon^4.$$

□

**Proof of Theorem 1.1** (First part). Using Lemma 5.2 with $\varepsilon = \xi$ and applying Corollary 5.1, we get an asymptotic representation

$$\sqrt{\pi} \mathbb{E}_{\vartheta} \omega^2(F_\vartheta, F) = \left(1 + \frac{1}{4n}\right) \left(\frac{1}{8} \mathbb{E} \xi^2 + \frac{1}{16} \mathbb{E} \xi^3 + c \mathbb{E} \xi^4\right) - \frac{1}{8n} + O\left(\frac{1}{n^2}\right)$$

for some quantity $c$ such that $0.01 \leq c \leq 3$. If additionally $X$ is isotropic, then $\mathbb{E} \langle X, Y \rangle^2 = n$, i.e. $\mathbb{E} \xi^2 = \frac{1}{n}$, and the representation is simplified to

$$\sqrt{\pi} \mathbb{E}_{\vartheta} \omega^2(F_\vartheta, F) = \left(1 + \frac{1}{4n}\right) \left(\frac{1}{16} \mathbb{E} \xi^3 + c \mathbb{E} \xi^4\right) + O\left(\frac{1}{n^2}\right),$$

thus removing the term of order $1/n$. Moreover, since $\mathbb{E} \xi^4 \leq \mathbb{E} |\xi|^3 \leq \mathbb{E} \xi^2 = \frac{1}{n}$, the fraction $\frac{1}{4n}$ may be removed from the brackets at the expense of the remainder term. Thus

$$\sqrt{\pi} \mathbb{E}_{\vartheta} \omega^2(F_\vartheta, F) = \frac{1}{16} \mathbb{E} \xi^3 + c \mathbb{E} \xi^4 + O\left(\frac{1}{n^2}\right),$$

which is exactly the expansion (1.3).

□

6. General Lower Bounds for the $L^2$-distance. **Proof of Theorem 1.2**

Proposition 4.1 may be used to establish the following general lower bound which will be the first step in the proof of Theorem 1.2. Recall that $Y$ denotes an independent copy of $X$.

**Proposition 6.1.** If $\mathbb{E} |X| \leq b \sqrt{n}$, then

$$\mathbb{E}_{\vartheta} \omega^2(F_\vartheta, F) \geq c_1 \mathbb{E} \rho \xi^4 - c_2 \frac{b}{n^2}, \quad (6.1)$$

where

$$\rho = \left(\frac{|X|^2 + |Y|^2}{2n}\right)^{1/2}, \quad \xi = \frac{2 \langle X, Y \rangle}{|X|^2 + |Y|^2}.$$
The argument employs two elementary lemmas.

**Lemma 6.2.** We have
\[ \mathbb{E} \left< X, Y \right>^2 \geq \frac{1}{n} \left( \mathbb{E} |X|^2 \right)^2. \] (6.2)

Without less of generality, suppose that the random vector \( X \) has a finite second moment. Moreover, by the invariance of the inequality (6.2) under linear orthogonal transformations of the space, we may assume that \( \mathbb{E} X_i X_j = \lambda_i \delta_{ij} \) where \( \lambda_i \)'s appear as eigenvalues of the covariance operator of \( X \). Since
\[ \mathbb{E} |X|^2 = \sum_{i=1}^{n} \lambda_i, \quad \mathbb{E} \left< X, Y \right>^2 = \sum_{i=1}^{n} \lambda_i^2, \]
(6.2) follows by applying Cauchy’s inequality.

**Lemma 6.3.** If \( \mathbb{E} |X|^p \) is finite for an integer \( p \geq 1 \), then, for any real number \( 0 \leq \alpha \leq p \),
\[ \mathbb{E} \left< X, Y \right>^2 \left( \frac{|X|^2 + |Y|^2}{|X|^2 + |Y|^2} \right)^\alpha \geq 0, \]
where the ratio is defined to be zero in case \( X = Y = 0 \). In addition, for \( \alpha \in [0, 2] \),
\[ \mathbb{E} \left< X, Y \right>^2 \left( \frac{|X|^2 + |Y|^2}{|X|^2 + |Y|^2} \right)^\alpha \geq \frac{1}{n} \mathbb{E} \frac{|X|^2 |Y|^2}{(|X|^2 + |Y|^2)^\alpha}. \]

**Proof.** First, let us note that
\[ \mathbb{E} \frac{|X|^p}{(|X|^2 + |Y|^2)^\alpha} \leq \mathbb{E} \frac{|X|^p}{|X|^\alpha} = (\mathbb{E} |X|^{p-\alpha})^2, \]
so, the expectation on the left is finite. Without loss of generality, we may assume that \( 0 < \alpha \leq p \) and that \( r = |X|^2 + |Y|^2 > 0 \) with probability 1. We use the identity
\[ \int_{0}^{\infty} e^{-rt^{1/\alpha}} dt = c_\alpha r^{-\alpha} \quad \text{where} \quad c_\alpha = \int_{0}^{\infty} e^{-s^{1/\alpha}} ds, \]
which gives
\[ c_\alpha \mathbb{E} \left< X, Y \right>^p r^{-\alpha} = \int_{0}^{\infty} \mathbb{E} \left< X, Y \right>^p e^{-rt^{1/\alpha}} dt. \]
Writing \( X = (X_1, \ldots, X_n) \) and \( Y = (Y_1, \ldots, Y_n) \), we have
\[ \mathbb{E} \left< X, Y \right>^p e^{-rt^{1/\alpha}} = \mathbb{E} \left< X, Y \right>^p e^{-t^{1/\alpha}(|X|^2 + |Y|^2)} = \sum_{i_1, \ldots, i_p=1}^{n} \left( \mathbb{E} X_{i_1} \ldots X_{i_p} e^{-t^{1/\alpha} |X|^2} \right)^2, \]
which shows that the left expectation is always non-negative. Integrating over \( t > 0 \), this proves the first assertion.

For the second assertion, write
\[ c_\alpha \mathbb{E} \left< X, Y \right>^2 r^{-\alpha} = \int_{0}^{\infty} \mathbb{E} \left< X, Y \right>^2 e^{-t^{1/\alpha}(|X|^2 + |Y|^2)} dt = \int_{0}^{\infty} \mathbb{E} \left< X_t, Y_t \right>^2 dt, \]
where
where
\[ X_t = e^{-t^{1/\alpha}|X|^2/2} X, \quad Y_t = e^{-t^{1/\alpha}|Y|^2/2} Y. \]

Since \( Y_t \) represents an independent copy of \( X_t \), one may apply Lemma 6.2 which gives
\[ \mathbb{E} \langle X_t, Y_t \rangle^2 \geq \frac{1}{n} \mathbb{E} |X_t|^2 |Y_t|^2. \]

Hence,
\[
\int_0^\infty \mathbb{E} \langle X_t, Y_t \rangle^2 \, dt = \frac{1}{n} \int_0^\infty \mathbb{E} |X_t|^2 |Y_t|^2 \, dt = \frac{1}{n} \int_0^\infty \mathbb{E} |X|^2 |Y|^2 e^{-t^{1/\alpha}(|X|^2 + |Y|^2)} \, dt = \frac{c\alpha}{n} \mathbb{E} |X|^2 |Y|^2 r^{-\alpha}.
\]

\[ \square \]

**Proof of Proposition 6.1.** Let us return to the representation (4.3) in Proposition 4.1 and write
\[ \mathbb{E}_\theta \omega^2(F_\theta, F) = \frac{1}{\sqrt{2\pi}} \mathbb{E} (R_0 + R_1) + \frac{Cb}{n^2}, \]
where
\[ R_0 = \frac{1}{8n^{3/2}} \frac{(|X|^2 - |Y|^2)^2}{(|X|^2 + |Y|^2)^{3/2}} \]
and
\[
R_1 = \frac{(|X|^2 + |Y|^2)^{1/2}}{\sqrt{n}} \left[ \left(1 + \frac{1}{4n}\right) (1 + \frac{1}{4n}) - \frac{|X - Y|}{\sqrt{n}} \right] \left[ \left(1 + \frac{1}{4n}\right) (1 - \sqrt{1 - \xi}) - \frac{1}{8n} \right]
\]
with the assumption that \( R_0 = 0 \) when \( X = Y = 0 \). Since \( |\xi| \leq 1 \), one may apply Lemma 5.2 which gives
\[ R_1 \geq \frac{(|X|^2 + |Y|^2)^{1/2}}{\sqrt{n}} \left[ \left(1 + \frac{1}{4n}\right) \left(\frac{1}{2} \xi + \frac{1}{8} \xi^2 + \frac{1}{16} \xi^3 + 0.01 \xi^4\right) - \frac{1}{8n} \right]. \]

The expectation of the terms on the right-hand side containing \( \xi \) and \( \xi^3 \) is non-negative according to Lemma 6.3 with \( \alpha = \frac{1}{2}, p = 1, \) and with \( \alpha = \frac{5}{2}, p = 3, \) respectively. Hence, removing the unnecessary factor \( 1 + \frac{1}{4n} \), we get
\[
\mathbb{E}_\theta \omega^2(F_\theta, F) \geq \frac{1}{\sqrt{2\pi}} \mathbb{E} R_0 + \frac{1}{\sqrt{2\pi}} \mathbb{E} \left(\frac{|X|^2 + |Y|^2)^{1/2}}{8\sqrt{n}} \right) \left(\xi^2 - \frac{1}{n}\right) + c_1 \mathbb{E} \left(\frac{|X|^2 + |Y|^2)^{1/2}}{\sqrt{n}} \right) \xi^4 - c_2 \frac{b}{n^2}. \tag{6.3}
\]

Now, by the second inequality of Lemma 6.3 applied with \( \alpha = 3/2, p = 2, \) we have
\[
\mathbb{E} (|X|^2 + |Y|^2)^{1/2} \xi^2 \geq \frac{4 \mathbb{E} \frac{(X,Y)^2}{(|X|^2 + |Y|^2)^{3/2}}}{\mathbb{E} \frac{|X|^2 |Y|^2}{(|X|^2 + |Y|^2)^{3/2}}},
\]
This gives

\[
\mathbb{E} \frac{(|X|^2 + |Y|^2)^{1/2}}{8\sqrt{n}} (\xi^2 - \frac{1}{n}) \geq \frac{1}{8n^{3/2}} \mathbb{E} \left[ \frac{4|X|^2|Y|^2}{(|X|^2 + |Y|^2)^{3/2}} - (|X|^2 + |Y|^2)^{1/2} \right] \\
= - \frac{1}{8n^{3/2}} \mathbb{E} \frac{(|X|^2 - |Y|^2)^2}{(|X|^2 + |Y|^2)^{3/2}} = -\mathbb{E}R_0.
\]

Thus, the summand \(\mathbb{E}R_0\) in (6.3) neutralizes the second expectation, and we are left with the term containing \(\xi^4\).

**Proof of Theorem 1.2.** We apply Proposition 6.1. By the assumption, \(\mathbb{E}\rho^2 = 1\) and \(\text{Var}(\rho^2) = \frac{1}{2n} \sigma_4^2\), where \(\sigma_4^2 = \frac{1}{n} \text{Var}(|X|^2)\). Using

\[
2 \langle X, Y \rangle = |X|^2 + |Y|^2 - |X - Y|^2, \quad \xi = 1 - \frac{|X - Y|^2}{|X|^2 + |Y|^2},
\]

we have

\[
\xi^4 \geq (1 - \alpha)^4 1_{\{|X - Y|^2 \leq \alpha (|X|^2 + |Y|^2)\}} \\
\geq (1 - \alpha)^4 1_{\{|X - Y|^2 \leq \alpha \lambda n, |X|^2 + |Y|^2 \geq \lambda n\}}, \quad 0 < \alpha, \lambda < 1.
\]

On the set \(|X|^2 + |Y|^2 \geq \lambda n\) necessarily \(\rho^2 \geq \frac{\lambda}{n^2}\), so

\[
\mathbb{E}\rho \xi^4 \geq \frac{(1 - \alpha)^4}{\sqrt{2}} \sqrt{\lambda} \mathbb{P}\{|X - Y|^2 \leq \alpha \lambda n, |X|^2 + |Y|^2 \geq \lambda n\} \\
\geq \frac{(1 - \alpha)^4}{\sqrt{2}} \sqrt{\lambda} \left( \mathbb{P}\{|X - Y|^2 \leq \alpha \lambda n\} - \mathbb{P}\{|X|^2 + |Y|^2 \leq \lambda n\} \right).
\]

But, by Chebyshev’s inequality

\[
\mathbb{P}\{|X|^2 \leq \lambda n\} = \mathbb{P}\{n - |X|^2 \geq (1 - \lambda) n\} \leq \frac{\text{Var}(|X|^2)}{(1 - \lambda)^2 n^2} = \frac{\sigma_4^2}{(1 - \lambda)^2 n},
\]

implying that

\[
\mathbb{P}\{|X|^2 + |Y|^2 \leq \lambda n\} \leq \left( \mathbb{P}\{|X|^2 \leq \lambda n\} \right)^2 \leq \frac{1}{(1 - \lambda)^4} \frac{\sigma_4^2}{n^2}.
\]

Hence

\[
\mathbb{E}\rho \xi^4 \geq \frac{(1 - \alpha)^4}{\sqrt{2}} \sqrt{\lambda} \left( \mathbb{P}\{|X - Y|^2 \leq \alpha \lambda n\} - \frac{1}{(1 - \lambda)^4} \frac{\sigma_4^2}{n^2} \right).
\]

Choosing, for example, \(\alpha = \lambda = \frac{1}{2}\), we get

\[
\mathbb{E}\rho \xi^4 \geq \frac{1}{32} \mathbb{P}\{|X - Y|^2 \leq \frac{1}{4} n\} - \frac{\sigma_4^2}{2n^2}.
\]

It remains to apply (6.1) with \(b = 1\) and replace \(F\) with \(\Phi\) on the basis of (2.3).

**7. Lipschitz Systems**

While upper bounds of order \(n^{-1/2}\) for the \(L^2\)-distance \(\omega(F_0, F)\) (on average) are provided in (1.2) and in the more general inequality (3.5) of Proposition 3.1, in this section we focus on conditions that provide similar lower bounds, as a consequence of Theorem 1.2.
Let $L$ be a fixed measurable function on the underlying probability space $(\Omega, \mathcal{F}, \mathbb{P})$. We will say that the system $X_1, \ldots, X_n$ of random variables on $(\Omega, \mathcal{F}, \mathbb{P})$, or the random vector $X = (X_1, \ldots, X_n)$ in $\mathbb{R}^n$ satisfies a Lipschitz condition with a parameter function $L$, if

$$\max_{1 \leq k \leq n} |X_k(t) - X_k(s)| \leq n |L(t) - L(s)|, \quad t, s \in \Omega. \quad (7.1)$$

When $\Omega$ is an interval of the real line (finite or not), and $L(t) = Lt$ where $L > 0$ is a real number, this condition means that every function $X_k$ in the system has a Lipschitz semi-norm at most $Ln$.

As before, we use the variance functional $\sigma_k^2 = \frac{1}{n} \text{Var}(|X|^2)$.

**Proposition 7.1.** Suppose that $\mathbb{E}|X|^2 = n$. If the random vector $X$ satisfies the Lipschitz condition with a parameter function $L$, then

$$\mathbb{E}_\theta \omega^2(F_\theta, F) \geq \frac{c_L}{n} - \frac{c_0 (1 + \sigma_k^4)}{n^2}$$

with some absolute constant $c_0 > 0$ and with a constant $c_L$ depending on the distribution of $L$ only. Moreover, if $L$ has finite second moment, then with some absolute constant $c_1 > 0$

$$\mathbb{E}_\theta \omega^2(F_\theta, F) \geq \frac{c_1}{n\sqrt{\text{Var}(L)}} - \frac{c_0 (1 + \sigma_k^4)}{n^2}. \quad (7.3)$$

Note that, if $X_1, \ldots, X_n$ form an orthonormal system in $L^2(\Omega, \mathcal{F}, \mathbb{P})$, i.e., the random vector $X$ is isotropic, and if $L$ has finite second moment $\|L\|_2^2 = \mathbb{E}L^2$, then this moment has to be bounded from below by a multiple of $1/n^2$. Indeed, integrating the inequality $|X_k(t) - X_k(s)|^2 \leq n^2 |L(t) - L(s)|^2$ over the product measure $\mathbb{P} \otimes \mathbb{P}$, we obtain a lower bound

$$n^2 \text{Var}(L) \geq \text{Var}(X_k) = 1 - (\mathbb{E}X_k)^2.$$

Summing over all $k \leq n$ and using Bessel’s inequality $\sum_{k=1}^n (\mathbb{E}X_k)^2 \leq 1$, we get

$$\text{Var}(L) \geq \frac{n - 1}{n^3} \geq \frac{1}{2n^2} \quad (n \geq 2).$$

The Lipschitz condition (7.1) guarantees the validity of the following property, which can be combined with Theorem 1.2 to obtain (7.2)-(7.3).

**Lemma 7.2.** Suppose that the random vector $X = (X_1, \ldots, X_n)$ satisfies the Lipschitz condition with the parameter function $L$. If $Y$ is an independent copy of $X$, then

$$\mathbb{P}\{|X - Y|^2 \leq \lambda n\} \geq \frac{c\sqrt{\lambda}}{n}, \quad 0 \leq \lambda \leq 1,$$

where the constant $c > 0$ depends on the distribution of $L$ only. Moreover, if $L$ has finite second moment, then

$$\mathbb{P}\{|X - Y|^2 \leq \lambda n\} \geq \frac{\sqrt{\lambda}}{6n\sqrt{\text{Var}(L)}}, \quad 0 \leq \lambda \leq n^2 \text{Var}(L).$$

In turn, this lemma is based on the following general observation.

**Lemma 7.3.** If $\eta$ is an independent copy of a random variable $\xi$, then for any $\varepsilon_0 > 0$,

$$\mathbb{P}\{\xi - \eta \leq \varepsilon\} \geq c\varepsilon, \quad 0 \leq \varepsilon \leq \varepsilon_0,$$
with some constant $c > 0$ independent of $\varepsilon$. Moreover, if the standard deviation $\sigma = \sqrt{\text{Var}(\xi)}$ is finite, then

$$\mathbb{P}\{|\xi - \eta| \leq \varepsilon\} \geq \frac{1}{6\sigma} \varepsilon, \quad 0 \leq \varepsilon \leq \sigma.$$ 

**Proof.** The difference $\xi - \eta$ has a non-negative characteristic function $h(t) = |\psi(t)|^2$, where $\psi$ is the characteristic function of $\xi$. Denoting by $H$ the distribution function of $\xi - \eta$, we start with a general identity

$$\int_{-\infty}^{\infty} \hat{p}(x) dH(x) = \int_{-\infty}^{\infty} p(t)h(t) dt,$$

(7.4) which is valid for any integrable function $p(t)$ on the real line with Fourier transform $\hat{p}(x) = \int_{-\infty}^{\infty} e^{itx} p(t) dt$, $x \in \mathbb{R}$. Given $\varepsilon > 0$, here we take a standard pair

$$p(t) = \frac{1}{2\pi} \left(\sin \frac{tx}{2}\right)^2, \quad \hat{p}(x) = \frac{1}{\varepsilon} \left(1 - \frac{|x|}{\varepsilon}\right)^+, \quad$$

where we use the notation $a^+ = \max\{a, 0\}$. In this case,

$$\int_{-\infty}^{\infty} \hat{p}(x) dH(x) \leq \frac{1}{\varepsilon} \int_{[-\varepsilon, \varepsilon]} dH(x) = \frac{1}{\varepsilon} \mathbb{P}\{|\xi - \eta| \leq \varepsilon\}.$$

On the other hand, since the function $\frac{\sin u}{u}$ is decreasing in $0 < u < \frac{\pi}{2}$, we have

$$\int_{-\infty}^{\infty} p(t)h(t) dt \geq \frac{1}{2\pi} \left(2 \sin(1/2)\right)^2 \int_{-1/\varepsilon}^{1/\varepsilon} h(t) dt \geq \frac{1}{\pi} \int_{-1/\varepsilon}^{1/\varepsilon} h(t) dt.$$ 

Hence, whenever $0 < \varepsilon \leq \varepsilon_0$, by (7.4),

$$\mathbb{P}\{|\xi - \eta| \leq \varepsilon\} \geq \frac{\varepsilon}{\pi} \int_{-1/\varepsilon}^{1/\varepsilon} h(t) dt \geq \frac{\varepsilon}{\pi} \int_{-1/\varepsilon_0}^{1/\varepsilon_0} h(t) dt.$$

Since $h(t)$ is bounded away from zero near the origin, the first assertion follows.

One may quantify this statement in terms of the variance $\sigma^2 = \text{Var}(\xi)$ by using Taylor’s expansion for $h(t)$ about zero. Indeed, it gives $1 - h(t) \leq \sigma^2 t^2$, and thus for $\varepsilon \leq \varepsilon_0 = \sigma$,

$$\int_{-1/\varepsilon}^{1/\varepsilon} h(t) dt \geq \int_{-1/\sigma}^{1/\sigma} (1 - \sigma^2 t^2) dt = \frac{4}{3\sigma}.$$

Since $\frac{\varepsilon}{\pi} \cdot \frac{4}{3\sigma} \geq \frac{1}{6\sigma} \varepsilon$, the lemma is proved. \qed

**Proof of Lemma 7.2.** Let us equip the product space $\Omega^2 = \Omega \times \Omega$ with the product measure $\mathbb{P}^2 = \mathbb{P} \otimes \mathbb{P}$ and redefine $X$ on this new probability space as $X(t, s) = X(t)$, $(t, s) \in \Omega^2$. Then one can introduce an independent copy of $X$ in the form $Y(t, s) = X(s)$. By the Lipschitz condition,

$$|X(t, s) - Y(t, s)|^2 = \sum_{k=1}^{n} |X_k(t) - X_k(s)|^2 \leq n^3 |L(t) - L(s)|^2.$$ 

Hence, if $\eta$ is an independent copy of the random variable $\xi = L$, then

$$\mathbb{P}\{|X - Y|^2 \leq \lambda n\} \geq \mathbb{P}\{n^3 |\xi - \eta|^2 \leq \lambda n\} = \mathbb{P}\left\{|\xi - \eta| \leq \frac{\sqrt{\lambda}}{n}\right\}. $$
But, by Lemma 7.3 with ε₀ = 1, the latter probability is at least c n√Λ, where the constant c depends on L only (via its distribution). An application of the second inequality of Lemma 7.2 yields the second assertion.

To include more examples, let us now give a bit more general form of Lemma 7.2, assuming that (Ω, P) = (Ω₁ × Ω₂, P₁ ⊗ P₂) is a product probability space.

Lemma 7.4. Let \( X = (X₁, \ldots, Xₙ) : Ω \rightarrow \mathbb{R}^n \) be a random vector such that, for some measurable functions \( L₁ \) and \( L₂ \) defined on \( Ω₁ \) and \( Ω₂ \) respectively,

\[
\max_{1 \leq k \leq n} |X₁ (t₁, t₂) - X₁ (s₁, s₂)| \leq n |L₁ (t₁) - L₁ (s₁)| + |L₂ (t₂) - L₂ (s₂)|
\]

(7.5)

for all \( (t₁, t₂), (s₁, s₂) \in Ω \). If \( Y \) is an independent copy of \( X \), then

\[
P\{ |X - Y|^2 \leq \lambda n \} \geq \frac{c λ}{n}, \quad 0 \leq \lambda \leq 1,
\]

(7.6)

where the constant \( c > 0 \) depends on the distributions of \( L₁ \) and \( L₂ \) only.

Proof. Again, let us equip the product space \( Ω² = Ω \times Ω \) with the product measure \( P² = P \otimes P \) and put \( X(t, s) = X(t) \), \( Y(t, s) = X(s) \) for \( t = (t₁, t₂) \in Ω \) and \( s = (s₁, s₂) \in Ω \), so that \( Y \) is an independent copy of \( X \). By the Lipschitz condition (7.5), for any \( k \leq n \),

\[
|X₁ (t₁) - X₁ (s₁)|^2 \leq 2n^2 |L₁ (t₁) - L₁ (s₁)| + 2 |L₂ (t₂) - L₂ (s₂)|^2,
\]

so

\[
|X(t) - Y(s)|^2 = \sum_{k=1}^{n} |X₁ (t₁) - X₁ (s₁)|^2 \leq 2n^3 |L₁ (t₁) - L₁ (s₁)|^2 + 2n |L₂ (t₂) - L₂ (s₂)|^2.
\]

Putting \( L₁ (t₁, t₂) = L₁ (t₁) \) and \( L₂ (t₁, t₂) = L₂ (t₂) \), one may treat \( L₁ \) and \( L₂ \) as independent random variables. If \( L₁' \) is an independent copy of \( L₁ \) and \( L₂' \) is an independent copy of \( L₂ \), we obtain that

\[
P\{ |X - Y|^2 \leq \lambda n \} \geq P\{ n^2 |L₁ - L₁'|^2 + |L₂ - L₂'|^2 \leq \frac{λ}{2} \}
\]

\[
\geq P\{ n^2 |L₁ - L₁'|^2 \leq \frac{λ}{4} \} P\{ |L₂ - L₂'|^2 \leq \frac{λ}{4} \}
\]

\[
= P\{ |L₁ - L₁'| \leq \frac{1}{2n} \sqrt{λ} \} P\{ |L₂ - L₂'| \leq \frac{1}{2n} \sqrt{λ} \}.
\]

It remains to apply Lemma 7.3.

Let us now combine the inequality (1.8) of Theorem 1.2 with the inequality (7.6) applied with \( λ = \frac{1}{4} \). Then we obtain the following generalization of Proposition 7.1.

Proposition 7.5. Under the Lipschitz condition (7.5), we have

\[
Eθ \omega² (F₀, F) \geq \frac{c}{n} - \frac{c₀ (1 + σ₄¹)}{n²},
\]

where \( c₀ > 0 \) is an absolute constant, while \( c > 0 \) depends on the distributions of \( L₁ \) and \( L₂ \). A similar estimate also holds when \( F \) is replaced with the normal distribution function \( Φ \).
The last assertion follows from the inequality (2.3), cf. Corollary 2.2.

8. Berry-Esseen-type Bounds

We now turn to the study of the Kolmogorov distance

\[ \rho(F_\theta, F) = \sup_x |F_\theta(x) - F(x)|, \quad \theta \in \mathbb{S}^{n-1}, \]

between the distribution functions \( F_\theta \) of the weighted sums \( S_\theta = \langle X, \theta \rangle \) and the typical distribution function \( F = \mathbb{E}_\theta F_\theta \). We are mostly interested in bounding the second moment \( \mathbb{E}_\theta \rho^2(F_\theta, F) \). As in the case of the \( L^2 \)-distance, our basic tool will be a Fourier analytic approach relying upon a general Berry-Esseen-type bound

\[ c\rho(U,V) \leq \int_0^T \frac{|\hat{U}(t) - \hat{V}(t)|}{t} dt + \frac{1}{T} \int_0^T |\hat{V}(t)| dt, \quad T > 0, \quad (8.1)\]

where \( U \) and \( V \) may be arbitrary distribution functions on the line with characteristic functions \( \hat{U} \) and \( \hat{V} \) respectively (cf. e.g. [4], [25], [26]).

As before, we denote by \( f_\theta \) and \( f \) the characteristic functions associated to \( F_\theta \) and \( F \). Recall that \( \sigma_{2p} \)-functionals were defined in (2.2).

**Lemma 8.1.** If \( T \geq T_0 \geq 1 \), then for all \( p \geq 1 \),

\[ c_p \mathbb{E}_\theta \rho^2(F_\theta, F) \leq \int_0^1 \frac{\mathbb{E}_\theta |f_\theta(t) - f(t)|^2}{t^2} dt + \log T \int_0^{T_0} \frac{\mathbb{E}_\theta |f_\theta(t) - f(t)|^2}{t} dt + \log T \int_{T_0}^T \frac{\mathbb{E}_\theta |f_\theta(t)|^2}{t} dt + \frac{1}{T^2} + \frac{1 + \sigma_{2p}^2}{n^p}, \quad (8.2)\]

where the constants \( c_p > 0 \) depend on \( p \) only.

**Proof.** By (8.1), for any \( \theta \in \mathbb{S}^{n-1} \),

\[ c\rho(F_\theta, F) \leq \int_0^T \frac{|f_\theta(t) - f(t)|}{t} dt + \frac{1}{T} \int_0^T |f(t)| dt, \]

and squaring it, we get

\[ c\rho^2(F_\theta, F) \leq \left( \int_0^T \frac{|f_\theta(t) - f(t)|}{t} dt \right)^2 + \frac{1}{T^2} \left( \int_0^T |f(t)| dt \right)^2. \]

Let us split integration in the first integral into the intervals \([0, 1]\) and \([1, T]\). By Cauchy’s inequality,

\[ \left( \int_0^1 \frac{|f_\theta(t) - f(t)|}{t} dt \right)^2 \leq \int_0^1 \frac{|f_\theta(t) - f(t)|^2}{t^2} dt, \]

while

\[ \left( \int_1^T \frac{|f_\theta(t) - f(t)|}{t} dt \right)^2 \leq \log T \int_1^T \frac{|f_\theta(t) - f(t)|^2}{t} dt. \]
Hence
\[
c \rho^2(F_\theta, F) \leq \int_0^1 \frac{\left| f_\theta(t) - f(t) \right|^2}{t^2} \, dt + \log T \int_1^T \frac{\left| f_\theta(t) - f(t) \right|^2}{t} \, dt + \frac{1}{T^2} \left( \int_0^T |f(t)| \, dt \right)^2.
\]

Without an essential loss one may extend integration in the second integral to the larger interval \([0, T]\). Moreover, taking the expectation over \(\theta\), we then get
\[
c E_\theta \rho^2(F_\theta, F) \leq \int_0^1 \frac{E_\theta |f_\theta(t) - f(t)|^2}{t^2} \, dt + \log T \int_0^T \frac{E_\theta |f_\theta(t) - f(t)|^2}{t} \, dt + \frac{1}{T^2} \left( \int_0^T |f(t)| \, dt \right)^2.
\]

Again, one may split integration in the second last integral to the two intervals \([0, T_0]\) and \([T_0, T]\), so that to consider separately sufficiently large values of \(t\) for which \(|f_\theta(t)|\) is small enough (with high probability). More precisely, since \(f(t) = E_\theta f_\theta(t)\) and
\[
|f_\theta(t) - f(t)|^2 \leq 2 |f_\theta(t)|^2 + 2 |f(t)|^2,
\]
we have \(|f(t)|^2 \leq E_\theta |f_\theta(t)|^2\) and therefore
\[
E_\theta |f_\theta(t) - f(t)|^2 \leq 4 E_\theta |f_\theta(t)|^2.
\]

It remains to apply Lemma 2.4.

In order to control the last integral in (8.2), one may apply the upper bound (2.8) on \(J_n\) in the representation (3.2) to get that, for all \(t \in \mathbb{R}\),
\[
E_\theta |f_\theta(t)|^2 \leq 5 E e^{-t^2 |X - Y|^2 / 2n} + 4 e^{-n/12},
\]
where \(Y\) is an independent copy of the random vector \(X\). Splitting the last expectation to the event \(A = \{|X - Y|^2 \leq \frac{1}{4} n\}\) and its complement leads to
\[
E_\theta |f_\theta(t)|^2 \leq 5 e^{-t^2 / 8} + 4 e^{-n/12} + 5 P(A). \tag{8.3}
\]
The latter probability may further be estimated by using the moment functionals such as \(m_p\). To recall the argument (cf. also [8], Proposition 2.5), first note that, by (2.9) with \(\lambda = \frac{3}{4}\),
\[
P\left\{|X|^2 + |Y|^2 \leq \frac{3}{4} n\right\} \leq P\left\{|X|^2 \leq \frac{3}{4} n\right\} P\left\{|Y|^2 \leq \frac{3}{4} n\right\} \leq \frac{(4\sigma_p)^{2p}}{n^p}.
\]
On the other hand, by Markov’s inequality, assuming that \(p \geq 1\) is integer, we have
\[
P\left\{||X, Y| \geq \frac{1}{4} n\right\} \leq \frac{4^p E (X, Y)^{2p}}{n^{2p}} = \frac{4^p m_{2p}^{2p}}{n^p}.
\]
Since \(|X - Y|^2 \geq |X|^2 + |Y|^2 - 2 |X, Y|\), it follows that
\[
P(A) \leq P\left\{|X|^2 + |Y|^2 \leq \frac{3}{4} n\right\} + P\left\{||X, Y| \geq \frac{1}{4} n\right\} \leq \frac{4^p}{n^p} (m_{2p}^{2p} + \sigma_{2p}^{2p}).
\]
Returning to (8.3) and noting that necessarily $m_{2p} \geq m_2 \geq 1$ under the assumption that $\mathbb{E}|X|^2 = n$, we thus obtain that
\[
c_p \mathbb{E}_\theta |f_\theta(t)|^2 \leq \frac{m_{2p}^2 + \sigma_{2p}^2}{n^p} + e^{-\epsilon^2/8}.
\]
Using this bound, the inequality (8.2) is simplified:

**Lemma 8.2.** If the random vector $X$ in $\mathbb{R}^n$ satisfies $\mathbb{E}|X|^2 = n$, then for all $T \geq T_0 \geq 1$ and any integer $p \geq 1$,
\[
c_p \mathbb{E}_\theta \rho^2(F_\theta, F) \leq \int_0^1 \frac{\mathbb{E}_\theta |f_\theta(t) - f(t)|^2}{t^2} dt + \log T \int_0^{T_0} \frac{\mathbb{E}_\theta |f_\theta(t) - f(t)|^2}{t} dt
\]
\[+ (1 + \log T)^2 \frac{m_{2p}^2 + \sigma_{2p}^2}{n^p} + \frac{1}{T^2} + e^{-T_0^2/8} \tag{8.4}
\]
with constants $c_p$ depending on $p$ only.

**9. Quantitative Forms of Sudakov’s Theorem for the Kolmogorov Distance**

Let us specialize Lemma 8.2 to the value $p = 1$, assuming that the random vector $X$ is isotropic in $\mathbb{R}^n$ (so that $m_2 = 1$). If $\sigma_2$ is bounded, then choosing $T = 4n, \ T_0 = 4\sqrt{\log n}$, the last three terms in (8.4) produce a quantity of order at most $(\log n)^2/n$. In order to bound the integrals in (8.4), one may apply the classical Poincaré inequality on the unit sphere $S^{n-1}$
\[
\mathbb{E}_\theta |u(\theta)|^2 \leq \frac{1}{n-1} \mathbb{E}_\theta |\nabla u(\theta)|^2 \tag{9.1}
\]
to the mean zero functions $u_t(\theta) = f_\theta(t) - f(t)$. They are well defined and smooth on $\mathbb{R}^n$ for any fixed value $t \in \mathbb{R}$ and have gradients (by differentiating in (3.1)) given by
\[
\langle \nabla u_t(\theta), w \rangle = it \mathbb{E}\langle X, w \rangle e^{it\langle X, \theta \rangle}, \quad w \in \mathbb{C}^n,
\]
where we use the canonical inner product in the product complex space. By the isotropy assumption,
\[
|\langle \nabla u_t(\theta), w \rangle| \leq |t| \mathbb{E}|\langle X, w \rangle| \leq |t||w|
\]
for all $w$. Hence $|\nabla u_t(\theta)|^2 \leq t^2$ for any $\theta \in \mathbb{R}^n$, so that by (9.1),
\[
\mathbb{E}_\theta |f_\theta(t) - f(t)|^2 \leq \frac{t^2}{n-1}. \tag{9.2}
\]
Applying this inequality in (8.4) together with the first bound in (2.3) in order to replace $F$ with $\Phi$, we obtain:

**Proposition 9.1.** Given an isotropic random vector $X$ in $\mathbb{R}^n$,
\[
\mathbb{E}_\theta \rho^2(F_\theta, \Phi) \leq c(1 + \sigma_2^2) \frac{(\log n)^2}{n}.
\]
Since $\sigma_2 \leq \sigma_4$, we thus have

$$\left( \mathbb{E}_\theta \rho^2(F_\theta, \Phi) \right)^{1/2} \leq c \left( 1 + \sigma_4 \right) \frac{\log n}{\sqrt{n}}$$

(9.3)

which sharpens (1.1). The latter bound will be an essential step in the proof of Theorem 1.3, while (1.1) is not strong enough.

Let us now consider another scenario in Lemma 8.4, where the distribution of $X$ is supported on the sphere $\sqrt{n} \mathbb{S}^{n-1}$. In this case,

$$\mathbb{E}_\theta |f_\theta(t) - f(t)|^2 = \mathbb{E}_\theta |f_\theta(t)|^2 - |f(t)|^2 = \mathbb{E} J_n(t|X - Y|) - J_n(t\sqrt{n})^2$$

according to (3.3), while $\sigma_4 = 0$. Hence, in (8.4) with $p = 2$ we arrive at the following preliminary bound which is needed for the proof of Theorem 1.1 in its second part.

**Corollary 9.2.** Suppose that $|X| = \sqrt{n}$ a.s., and $Y$ is an independent copy of $X$. Then

$$c \mathbb{E}_\theta \rho^2(F_\theta, F) \leq \int_0^1 \frac{\Delta_n(t)}{t^2} dt + \log n \int_0^{\sqrt{n}\rho \log n} \frac{\Delta_n(t)}{t} dt + \left( \frac{\log n}{n^2} \right) m^4,$$

(9.4)

where

$$\Delta_n(t) = \mathbb{E} J_n(t|X - Y|) - J_n(t\sqrt{n})^2.$$

(9.5)

10. Proof of Theorem 1.1 for the Kolmogorov Distance

To study the integrals in (9.4), assume additionally that the random vector $X$ in $\mathbb{R}^n$ is isotropic and has mean zero. Focusing on the first integral, we need to develop an asymptotic bound on $\Delta_n(t)$ for $t \in [0, 1]$. Let $\xi = \frac{(X,Y)}{n}$, where $Y$ is an independent copy of $X$. Since $|X - Y|^2 = 2n(1 - \xi)$, (9.5) becomes

$$\Delta_n(t) = \mathbb{E} J_n(t\sqrt{2n(1 - \xi)}) - \left( J_n(t\sqrt{n}) \right)^2.$$

We use the asymptotic formula (2.7),

$$J_n(t\sqrt{n}) = \left( 1 - \frac{t^4}{4n} \right) e^{-t^2/2} + \varepsilon_n(t), \quad t \in \mathbb{R},$$

(10.1)

where $\varepsilon_n(t)$ denotes a quantity of the form $O(n^{-2} \min(1, t^4))$ with a universal constant in $O$. It implies a similar representation

$$\left( J_n(t\sqrt{n}) \right)^2 = \left( 1 - \frac{t^4}{2n} \right) e^{-t^2} + \varepsilon_n(t).$$

(10.2)

Since $|\xi| \leq 1$ a.s., we also have

$$J_n(t\sqrt{2n(1 - \xi)}) = \left( 1 - \frac{t^4}{n} (1 - \xi)^2 \right) e^{-t^2(1 - \xi)} + \varepsilon_n(t).$$

Hence, subtracting from $e^{t^2\xi}$ the linear term $1 + t^2\xi$ and adding, one may write

$$\Delta_n(t) = e^{-t^2} \mathbb{E} \left( \left( 1 - \frac{t^4}{n} (1 - \xi)^2 \right) e^{t^2\xi} - \left( 1 - \frac{t^4}{2n} \right) \right) + \varepsilon_n(t)$$

$$= e^{-t^2} \mathbb{E} (U + V) + \varepsilon_n(t)$$
with

\[ U = \frac{t^4}{n} \left( \frac{1}{2} - (1 - \xi)^2 \right) + \left( 1 - \frac{t^4}{n} \right) (1 - \xi)^2 \cdot t^2 \xi, \]

\[ V = \left( 1 - \frac{t^4}{n} \right) (1 - \xi^2) (e^{t^2 \xi} - 1 - t^2 \xi). \]

Using \( \mathbb{E} \xi = 0, \mathbb{E} \xi^2 = \frac{1}{n} \) and hence \( \mathbb{E} |\xi|^3 \leq \mathbb{E} \xi^2 \leq \frac{1}{n} \), we find that in the interval \( 0 \leq t \leq 1 \),

\[ \mathbb{E} U = -\frac{t^4}{2n} - \frac{t^4}{n^2} + \frac{2t^6}{n^2} - \frac{t^6}{n} \mathbb{E} \xi^3 = -\frac{t^4}{2n} + \varepsilon_n(t). \]

Next write

\[ V = W - \frac{t^4}{n} (1 - \xi^2) W, \quad W = e^{t^2 \xi} - 1 - t^2 \xi. \]

Using \(|e^x - 1 - x| \leq 2x^2\) for \(|x| \leq 1\), we have \(|W| \leq 2t^4 \xi^2\). Hence, the expected value of the second term in the representation for \( V \) does not exceed \( 8t^8/n^2 \). Moreover, by Taylor’s expansion,

\[ W = \frac{1}{2} t^4 \xi^2 + \frac{1}{6} t^6 \xi^3 + Rt^8 \xi^4, \quad R = \sum_{k=4}^{\infty} \frac{t^{2k-8}}{k!} \xi^{k-4}, \]

implying that

\[ \mathbb{E} W = \frac{t^4}{2n} + \frac{t^6}{6} \mathbb{E} \xi^3 + Ct^8 \mathbb{E} \xi^4 \]

where \( C \) is bounded by an absolute constant. Summing the two expansions, we arrive at

\[ \mathbb{E} (U + V) = \frac{t^6}{6} \mathbb{E} \xi^3 + Ct^8 \mathbb{E} \xi^4 + \varepsilon_n(t), \]

and therefore

\[ \int_0^1 \frac{\Delta_n(t)}{t^2} \, dt \leq c_1 \mathbb{E} \xi^3 + c_2 \mathbb{E} \xi^4 + O(n^{-2}). \]

Here \( \mathbb{E} \xi^4 \geq (\mathbb{E} \xi^2)^2 = n^{-2}, \) so the term \( O(n^{-2}) \) may be absorbed by the 4-th moment of \( \xi \). Since \( \mathbb{E} \xi^3 \geq 0 \), the bound (9.5) may be simplified to

\[ c \mathbb{E} \rho^2(F_\theta, F) \leq \mathbb{E} \xi^3 + \mathbb{E} \xi^4 + \log n \int_0^{4\sqrt{\log n}} \frac{\Delta_n(t)}{t} \, dt + \frac{(\log n)^2}{n^2} m_4^4, \]

that is,

\[ c \mathbb{E} \rho^2(F_\theta, F) \leq \log n \int_0^{4\sqrt{\log n}} \frac{\Delta_n(t)}{t} \, dt + \mathbb{E} \xi^3 + (\log n)^2 \mathbb{E} \xi^4. \quad (10.3) \]

Turning to the remaining integral (which is most important), let us express it in terms of the functions \( g_n(t) = J_n(t\sqrt{2n}) \) and

\[ \psi(\alpha) = \int_0^T \frac{g_n(\alpha t) - g_n(t)}{t} \, dt, \quad 0 \leq \alpha \leq \sqrt{2}, \quad T > 1, \]

which will be needed with \( T = 4\sqrt{\log n} \). Namely, we have

\[ \int_0^T \frac{\Delta_n(t)}{t} \, dt = \mathbb{E} \psi(\sqrt{1 - \xi}) + \int_0^T \frac{J_n(t\sqrt{2n}) - (J_n(t\sqrt{n}))^2}{t} \, dt. \quad (10.4) \]
To proceed, we need to develop a Taylor expansion for \( \xi \to \psi(\sqrt{1 - \xi}) \) around zero in powers of \( \xi \). Recall that \( g_n(t) \) represents the characteristic function of the random variable \( \sqrt{2n} \theta_1 \) on the probability space \((S^{n-1}, \mathcal{B}_{n-1})\). This already ensures that \( |g_n(t)| \leq 1 \) and

\[
|g'_n(t)| \leq \frac{1}{\sqrt{2n}} \mathbb{E} |\theta_1| \leq \sqrt{\frac{2}{n}} (\mathbb{E} \theta_1^2)^{1/2} = \sqrt{2}
\]

for all \( t \in \mathbb{R} \). Hence

\[
|g_n(\alpha t) - g_n(t)| \leq \sqrt{2} |\alpha - 1| |t| \leq 2 |t|,
\]

so that

\[
|\psi(\alpha)| \leq \int_0^1 \frac{|g_n(\alpha t) - g_n(t)|}{t} dt + \int_1^T \frac{|g_n(\alpha t) - g_n(t)|}{t} dt \leq 2 + 2 \log T < 4 \log T
\]

(since \( T > e \)). In addition, \( \psi(1) = 0 \) and

\[
\psi'(\alpha) = \int_0^T g'_n(\alpha t) dt = \frac{1}{\alpha} (g_n(\alpha T) - 1).
\]

Therefore, we arrive at another expression

\[
\psi(\alpha) = \int_1^\alpha \frac{g_n(T x) - 1}{x} dx = \int_1^\alpha \frac{g_n(T x)}{x} dx - \log \alpha.
\]

For \( |\varepsilon| \leq 1 \), let

\[
v(\varepsilon) = \int_1^{(1-\varepsilon)^{1/2}} \frac{g_n(T x)}{x} dx,
\]

\[
u(\varepsilon) = \psi((1-\varepsilon)^{1/2}) = v(\varepsilon) - \frac{1}{2} \log(1 - \varepsilon),
\]

so that \( \mathbb{E} \psi(\sqrt{1 - \xi}) = \mathbb{E} u(\xi) \). Applying the non-uniform bound \( |g_n(t)| \leq 5 (e^{-t^2} + e^{-n/12}) \), cf. (2.6), we have that, for \(-1 \leq \varepsilon \leq \frac{1}{2}\),

\[
|v(\varepsilon)| \leq \sup_{\frac{1}{\sqrt{n}} \leq x \leq \sqrt{2}} |g_n(T x)| \int_{\frac{1}{\sqrt{n}}}^{\sqrt{2}} \frac{1}{x} dx \leq \sup_{z \geq T/\sqrt{n}} |g_n(z)| \leq 5 (e^{-T^2/2} + e^{-n/12}) \leq \frac{c}{n^8},
\]

where the last inequality is specialized to the choice \( T = 4\sqrt{\log n} \). Using the Taylor expansion on the same interval for the log-function, we also have \( -\log(1 - \varepsilon) \leq \varepsilon + \frac{1}{2} \varepsilon^2 + \frac{1}{3} \varepsilon^3 + \frac{2}{3} \varepsilon^4 \).

Combining the two inequalities, we get

\[
u(\varepsilon) \leq \frac{1}{2} \varepsilon + \frac{1}{4} \varepsilon^2 + \frac{1}{6} \varepsilon^3 + \frac{1}{3} \varepsilon^4 + \frac{c}{n^8}, \quad -1 \leq \varepsilon \leq \frac{1}{2}.
\]

In order to involve the remaining interval \( \frac{1}{2} \leq \varepsilon \leq 1 \) in the inequality of a similar type, recall that \( |u(\varepsilon)| \leq 4 \log T \) for all \( |\varepsilon| \leq 1 \). Hence, the above inequality will hold automatically, if we increase the coefficient 1/3 in front of \( \varepsilon^4 \) to a suitable multiple of \( \log T \). As a result, we obtain the desired inequality on the whole segment, that is,

\[
u(\varepsilon) \leq \frac{1}{2} \varepsilon + \frac{1}{4} \varepsilon^2 + \frac{1}{6} \varepsilon^3 + c \log T \varepsilon^4 + \frac{c}{n^8}, \quad -1 \leq \varepsilon \leq 1.
\]

In particular,

\[
\psi(\sqrt{1 - \xi}) \leq \frac{1}{2} \xi + \frac{1}{4} \xi^2 + \frac{1}{6} \xi^3 + c \log T \xi^4 + \frac{c}{n^8},
\]
and taking the expectation, we get
\[ E\psi(\sqrt{1-\xi}) \leq \frac{1}{4n} + \frac{1}{6} \mathbb{E}\xi^3 + c \log T \mathbb{E}\xi^4, \] (10.5)
where the term \( cn^{-8} \) was absorbed by the 4-th moment of \( \xi \).

Now, let us turn to the integral
\[ I_n = \int_0^T \frac{J_n(t\sqrt{2n}) - (J_n(t\sqrt{n}))^2}{t} \, dt, \]
appearing in (10.4), and recall the asymptotic formulas (10.1)-(10.2). After integration, the remainder term \( \varepsilon_n(t) = O(n^{-2 \min(1, t^4)}) \) will create an error of order at most \( n^{-2} \log T \), up to which \( I_n \) is equal to
\[ -\int_0^T \frac{t^4}{2n} e^{-t^2} \, dt = -\frac{1}{4n} \left( 1 - (T^2 + 1) e^{-T^2} \right) = -\frac{1}{4n} + o(n^{-15}). \]
Thus,\[ I_n = -\frac{1}{4n} + O(n^{-2} \log T). \]
Applying this expansion together with (10.5) in (10.4), we therefore obtain that
\[ \int_0^T \frac{\Delta_n(t)}{t} \, dt \leq \frac{1}{6} \mathbb{E}\xi^3 + c \log T \mathbb{E}\xi^4. \]

One can now apply this estimate in (10.3), and then we eventually arrive at
\[ \mathbb{E}_\theta \rho^2(F_\theta, F) \leq c_1 (\log n) \mathbb{E}\xi^3 + c_2 (\log n)^2 \mathbb{E}\xi^4. \]
By (2.3) with \( p = \infty \), a similar inequality remains to hold for the standard normal distribution function \( \Phi \) in place of \( F \). This proves the inequality (1.4).

11. Relations between \( L^1 \), \( L^2 \) and Kolmogorov Distances

Given a random vector \( X \) in \( \mathbb{R}^n \), let us now compare the \( L^2 \) and \( L^\infty \) distances on average, between the distributions \( F_\theta \) of the weighted sums \( \langle X, \theta \rangle \) and the typical distribution \( F = \mathbb{E}_\theta F_\theta \). Such information will be needed to derive appropriate lower bounds on \( \mathbb{E}_\theta \rho(F_\theta, F) \).

**Proposition 11.1.** If \( |X| \leq b \sqrt{n} \) a.s., then, for any \( \alpha \in [1, 2] \),
\[ b^{-\alpha/2} \mathbb{E}_\theta \omega^\alpha(F_\theta, F) \leq 14 (\log n)^{\alpha/4} \mathbb{E}_\theta \rho^\alpha(F_\theta, F) + \frac{8}{n^4}. \] (11.1)

As will be clear from the proof, at the expense of a larger coefficient in front of \( \log n \), the last term \( n^{-4} \) can be replaced by \( n^{-\beta} \) for any prescribed value of \( \beta \).

A relation similar to (11.1) is also true for the Kantorovich or \( L^1 \)-distance
\[ W(F_\theta, F) = \int_{-\infty}^{\infty} |F_\theta(x) - F(x)| \, dx \]
in place of \( L^2 \). We state it for the case \( \alpha = 1 \).
Proposition 11.2. If $|X| \leq b\sqrt{n} \ a.s.$, then

$$
\mathbb{E}_\theta W(F_\theta, F) \leq 14 \sqrt{\log n} \mathbb{E}_\theta \rho(F_\theta, F) + \frac{8b}{n^4}.
$$

(11.2)

Proof. Put $R_\theta(x) = F_\theta(-x) + (1 - F_\theta(x))$ for $x > 0$ and define similarly $R$ on the basis of $F$. Using

$$(F_\theta(-x) - F(-x))^2 \leq F_\theta(-x)^2 + F(-x)^2,$$

$$(F_\theta(x) - F(x))^2 \leq (1 - F_\theta(x))^2 + (1 - F(x))^2,$$

we have

$$(F_\theta(-x) - F(-x))^2 + (F_\theta(x) - F(x))^2 \leq R_\theta(x)^2 + R(x)^2.$$  

Hence, given $T > 0$ (to be specified later on), we have

$$
\omega^2(F_\theta, F) = \int_{-T}^{T} (F_\theta(x) - F(x))^2 \, dx + \int_{|x| \geq T} (F_\theta(x) - F(x))^2 \, dx
$$

$$
\leq 2T \rho^2(F_\theta, F) + \int_{T}^{\infty} R_\theta(x)^2 \, dx + \int_{T}^{\infty} R(x)^2 \, dx.
$$

It follows that, for any $\alpha \in [1, 2]$,

$$
\omega^\alpha(F_\theta, F) \leq (2T)\frac{\alpha}{2} \rho^\alpha(F_\theta, F) + \left( \int_{T}^{\infty} R_\theta(x)^2 \, dx \right)^{\frac{\alpha}{2}} + \left( \int_{T}^{\infty} R(x)^2 \, dx \right)^{\frac{\alpha}{2}},
$$

and therefore, by Jensen’s inequality,

$$
\mathbb{E}_\theta \omega^\alpha(F_\theta, F) \leq (2T)\frac{\alpha}{2} \mathbb{E}_\theta \rho^\alpha(F_\theta, F)
$$

$$
+ \left( \int_{T}^{\infty} \mathbb{E}_\theta R_\theta(x)^2 \, dx \right)^{\frac{\alpha}{2}} + \left( \int_{T}^{\infty} \mathbb{E}_\theta R(x)^2 \, dx \right)^{\frac{\alpha}{2}}.
$$

Next, by Markov’s inequality, for any $x > 0$ and $p \geq 1$,

$$
R_\theta(x)^2 \leq \left( \frac{\mathbb{E} |\langle X, \theta \rangle|^p}{x^p} \right)^2 \leq \frac{\mathbb{E} |\langle X, \theta \rangle|^{2p}}{x^{2p}}
$$

and

$$
\mathbb{E}_\theta R_\theta(x)^2 \leq \left( \frac{\mathbb{E} |\langle X, \theta \rangle|^p}{x^p} \right)^2 \leq \frac{\mathbb{E}_\theta \mathbb{E} |\langle X, \theta \rangle|^{2p}}{x^{2p}}.
$$

Since $R = \mathbb{E}_\theta R_\theta$, a similar inequality holds true for $R$ as well (by Cauchy’s inequality). Hence

$$
\mathbb{E}_\theta \omega^\alpha(F_\theta, F) \leq (2T)\frac{\alpha}{2} \mathbb{E}_\theta \rho^\alpha(F_\theta, F) + 2 \left( \mathbb{E}_\theta \mathbb{E} |\langle X, \theta \rangle|^{2p} \int_{T}^{\infty} \frac{1}{x^{2p}} \, dx \right)^{\frac{\alpha}{2}}.
$$

When $\theta = (\theta_1, \ldots, \theta_n)$ is treated as a random vector with distribution $\mathcal{N}_{n-1}$, which is independent of $X$, the inner product $\langle X, \theta \rangle$ has the same distribution as the random variable $|X| \theta_1$. Therefore, recalling Lemma 2.5,

$$
\mathbb{E}_\theta \mathbb{E} |\langle X, \theta \rangle|^{2p} = \mathbb{E} |X|^{2p} \mathbb{E}_\theta |\theta_1|^{2p} \leq 2 (2b^2 p)^p,
$$

so that

$$
2 \left( \mathbb{E}_\theta \int_{T}^{\infty} \mathbb{E} |\langle X, \theta \rangle|^{2p} \, dx \right)^{\frac{\alpha}{2}} \leq \frac{2^{\frac{\alpha}{2}+1}}{(2p-1)^{\frac{\alpha}{2}}} \left( \frac{2b^2 p}{T} \right)^{\frac{2p}{2}}.
$$

Thus,

$$
\mathbb{E}_\theta \omega^\alpha(F_\theta, F) \leq (2T)\frac{\alpha}{2} \mathbb{E}_\theta \rho^\alpha(F_\theta, F) + \frac{2^{\frac{\alpha}{2}+1}}{(2p-1)^{\frac{\alpha}{2}}} T^{\frac{\alpha}{2}} \left( \frac{2b^2 p}{T^2} \right)^{\frac{2p}{2}}.
$$
Let us choose \( T = 2b\sqrt{p} \) in which case the above inequality becomes

\[
\mathbb{E}_\theta \omega^\alpha(F_\theta, F) \leq (4b\sqrt{p})^{\frac{\alpha}{2}} \mathbb{E}_\theta \rho^\alpha(F_\theta, F) + \frac{2^{\alpha+1}}{(2p-1)^{\frac{\alpha}{2}}} (b\sqrt{p})^{\frac{\alpha}{2}} 2^{-\frac{\alpha p}{2}}.
\]

To simplify, one can use \( \sqrt{p} \leq 2p - 1 \) for \( p \geq 1 \) together with \( 2^{\alpha+1} \leq 8 \) and \( 2^{-\frac{\alpha p}{2}} \leq 2^{-\frac{p}{2}} \) (since \( 1 \leq \alpha \leq 2 \)), which leads to

\[
\mathbb{E}_\theta \omega^\alpha(F_\theta, F) \leq (4b\sqrt{p})^{\frac{\alpha}{2}} \mathbb{E}_\theta \rho^\alpha(F_\theta, F) + 8b^{\frac{\alpha}{2}} 2^{-\frac{p}{2}}.
\]

Finally, choosing \( p = p_n = (8 \log n)/\log 2 \), we arrive at (11.1).

Now, turning to (11.2), we use the same functions \( R_\theta \) and \( R \) as before and write

\[
W(F_\theta, F) = \int_{-T}^{T} |F_\theta(x) - F(x)| \, dx + \int_{|x| \geq T} |F_\theta(x) - F(x)| \, dx
\]

\[
\leq 2T \rho(F_\theta, F) + \int_{T}^{\infty} R_\theta(x) \, dx + \int_{T}^{\infty} R(x) \, dx,
\]

which gives

\[
\mathbb{E}_\theta W(F_\theta, F) \leq 2T \mathbb{E}_\theta \rho(F_\theta, F) + 2 \int_{T}^{\infty} R(x) \, dx.
\]

By Markov’s inequality, for any \( x > 0 \) and \( p > 1 \),

\[
R_\theta(x) \leq \frac{\mathbb{E} | \langle X, \theta \rangle |^p}{x^p}, \quad R(x) = \mathbb{E}_\theta R_\theta(x) \leq \frac{\mathbb{E}_\theta \mathbb{E} | \langle X, \theta \rangle |^p}{x^p}.
\]

Hence

\[
\mathbb{E}_\theta W(F_\theta, F) \leq 2T \mathbb{E}_\theta \rho(F_\theta, F) + 2 \mathbb{E}_\theta \mathbb{E} | \langle X, \theta \rangle |^p \int_{T}^{\infty} \frac{1}{x^p} \, dx.
\]

Here, one may use once more the bound (2.10), which yields

\[
\mathbb{E}_\theta \mathbb{E} | \langle X, \theta \rangle |^p = \mathbb{E} | X |^p \mathbb{E}_\theta | \theta_1 |^p \leq 2(b^2 p)^{p/2}
\]

and

\[
\mathbb{E}_\theta W(F_\theta, F) \leq 2T \mathbb{E}_\theta \rho(F_\theta, F) + \frac{4}{p - 1} \frac{(b^2 p)^{p/2}}{T^{p-1}}.
\]

Let us take \( T = 2b\sqrt{p} \) in which case the above inequality becomes

\[
\mathbb{E}_\theta W(F_\theta, F) \leq 4b\sqrt{p} \mathbb{E}_\theta \rho(F_\theta, F) + 8b \frac{\sqrt{p}}{p - 1} 2^{-p}.
\]

Here we arrive at (11.2), by choosing again \( p = p_n \) and using \( \sqrt{p_n} < p_n - 1 \). \( \square \)

12. Lower Bounds. Proof of Theorem 1.3

A lower bound on \( \mathbb{E}_\theta \rho^2(F_\theta, \Phi) \) which would be close to the upper bound (1.4) may be given with the help of the lower bound on \( \mathbb{E}_\theta \omega^2(F_\theta, \Phi) \). More precisely, this can be done in the case where the quantity \( \frac{1}{n^{1/2}} m_3^3 + \frac{1}{n^2} m_4^4 \) asymptotically dominates \( n^{-2} \) (in particular, when \( m_4 \) is essentially larger than 1). Combining the asymptotic expansion (1.3) of Theorem 1.1 with the bound (11.1) of Proposition 11.1 (for \( \alpha = 2 \)), and recalling the second relation in (2.3) on the normal approximation for the typical distribution \( F \), we therefore obtain:
Proposition 12.1. If $X$ is an isotropic random vector in $\mathbb{R}^n$ with mean zero and such that $|X| = \sqrt{\bar{n}}$ a.s., then
\[
\sqrt{\log n} \; \mathbb{E}_\theta \rho^2(F_\theta, \Phi) \geq \frac{c_1}{n^{3/2}} m_3^3 + \frac{c_2}{n^2} m_4^4 - \frac{c_3}{n^2}.
\] (12.1)

The relation (11.2) for the Kantorovich distance $W$ may be used to answer the following question: Is it possible to sharpen the lower bound (12.1) by replacing $\mathbb{E}_\theta \rho^2(F_\theta, \Phi)$ with $\mathbb{E}_\theta \rho(F_\theta, \Phi)$? To this aim, we will need an additional information about moments of $\omega(F_\theta, F)$ of order higher than 2.

Lemma 12.2. If $X$ is isotropic and satisfies $|X| \leq b\sqrt{n}$, then
\[
(c_0 \omega(X, \theta))^3 \leq (1 + \sigma_4) \sqrt{\mathbb{E}_\theta (\log n)^5/4}. \] (12.2)

Proof. For any distribution function $G$, the function of the form $g(\theta) = W(F_\theta, G)$ has a Lipschitz semi-norm $\|g\|_{\text{Lip}} \leq 1$. Therefore, it admits a subgaussian large deviation bound
\[
s_{n-1}\{W(F_\theta, G) \geq m + r\} \leq e^{-(n-1)r^2/2}, \quad r \geq 0,
\] (12.3)
where $m = \mathbb{E}_\theta W(F_\theta, G)$. Indeed, consider the elementary representation
\[
W(F_\theta, G) \equiv \int_{-\infty}^{\infty} |F_\theta(x) - G(x)| \, dx
= \sup_u \left[ \int_{-\infty}^{\infty} u \, dF_\theta - \int_{-\infty}^{\infty} u \, dG \right],
\]
where the supremum is running over all functions $u$ on $\mathbb{R}$ with $\|u\|_{\text{Lip}} \leq 1$. For any such $u$,
\[
H_u(\theta) = \int_{-\infty}^{\infty} u \, dF_\theta = \mathbb{E} u(\langle X, \theta \rangle)
\]
is Lipschitz on $\mathbb{R}^n$ and therefore on $\mathbb{S}^{n-1}$. Moreover, $\|g\|_{\text{Lip}} \leq \sup_u \|H_u\|_{\text{Lip}} \leq 1$.

Hence, (12.3) is fulfilled as a consequence of the well-known fact that the logarithmic Sobolev constant for the uniform distribution on the unit sphere is equal to $n - 1$ (cf. [23]). In particular, for any $r \geq 0$,
\[
s_{n-1}\{W(F_\theta, F) \geq m + r\} \leq e^{-(n-1)r^2/2}
\]
with $m = \mathbb{E}_\theta W(F_\theta, F)$. In turn, the latter ensures that, for any $p \geq 2$,
\[
\left( \mathbb{E}_\theta W(F_\theta, F)^p \right)^{1/p} \leq m + \frac{\sqrt{p}}{\sqrt{n-1}}. \] (12.4)
For the proof, put $\xi = (W(F_\theta, F) - m)^+$. Using $\Gamma(x+1) \leq x^x$ with $x = p/2 \geq 1$, we have
\[
\mathbb{E}_\theta \xi^p = \int_0^\infty s_{n-1}\{\xi \geq r\} \, dr^p \leq \int_0^\infty e^{-(n-1)r^2/2} \, dr^p
= \left( \frac{\sqrt{2}}{\sqrt{n-1}} \right)^p \Gamma \left( \frac{p}{2} + 1 \right) \leq \left( \frac{\sqrt{p}}{\sqrt{n-1}} \right)^p \equiv A.
\]
Thus, $\|\xi\|_p = (\mathbb{E}_\theta \xi^p)^{1/p} \leq A$. Since $W(F_\theta, F) \leq \xi + m$, we conclude, by the triangle inequality, that $\|W(F_\theta, F)\|_p \leq \|\xi\|_p + m \leq A + m$, that is, (12.4) holds.
Let us proceed with one elementary general inequality, connecting the three distances,
\[
\omega^2(F_\theta, F) = \int_{-\infty}^{\infty} (F_\theta(x) - F(x))^2 \, dx
\]
\[
\leq \int_{-\infty}^{\infty} \sup_x |F_\theta(x) - F(x)| \, (|F_\theta(x) - F(x)| \, dx = \rho(F_\theta, F) W(F_\theta, F).
\]
Putting \(\omega = \omega(F_\theta, F), W = W(F_\theta, F), \rho = \rho(F_\theta, F)\), we thus have \(\omega^3 \leq W^{3/2} \rho^{3/2}\) and, by Hölder’s inequality with exponents \(p = 4\) and \(q = 4/3\),
\[
(\mathbb{E}_\theta \omega^3)^{1/3} \leq (\mathbb{E}_\theta W^6)^{1/12} (\mathbb{E}_\theta \rho^2)^{1/4}.
\]
By (12.4) with \(p = 6\), we have
\[
(\mathbb{E}_\theta W^6)^{1/6} \leq \mathbb{E}_\theta W + \frac{4}{\sqrt{n}},
\]
so that
\[
(\mathbb{E}_\theta \omega^3)^{1/3} \leq \left(\mathbb{E}_\theta W + \frac{4}{\sqrt{n}}\right)^{1/2} (\mathbb{E}_\theta \rho^2)^{1/4}.
\]
Applying Proposition 11.2 and noting that necessarily \(b \geq 1\), we get
\[
(\mathbb{E}_\theta \omega^3)^{1/3} \leq 4\sqrt{b} \left(\sqrt{\log n} \, \mathbb{E}_\theta \rho + \frac{1}{\sqrt{n}}\right)^{1/2} (\mathbb{E}_\theta \rho^2)^{1/4}.
\]
It remains to apply here the inequality (9.3) with \(F\) in place of \(\Phi\), i.e.
\[
\mathbb{E}_\theta \rho(F_\theta, F) \leq (\mathbb{E}_\theta \rho^2(F_\theta, F))^{1/2} \leq c (1 + \sigma_1) \log n \frac{1}{\sqrt{n}}.
\]
\[\square\]

Let us now explain how the upper bound (12.2) can be used to refine the lower bound (12.1). The argument is based on the following general elementary observation. Given a random variable \(\xi\), introduce the \(L^p\) norms \(||\xi||_p = (\mathbb{E} |\xi|^p)^{1/p}\).

**Lemma 12.3.** If \(\xi \geq 0\) with \(0 < ||\xi||_3 < \infty\), then
\[
\mathbb{E} \xi \geq \frac{1}{\mathbb{E} \xi^3} (\mathbb{E} \xi^2)^2.
\]
Moreover,
\[
\mathbb{P}\{\xi \geq \frac{1}{\sqrt{2}} ||\xi||_2\} \geq \frac{1}{8} \left(\frac{||\xi||_2}{||\xi||_3}\right)^6.
\]

Thus, in the case where \(||\xi||_2\) and \(||\xi||_3\) are almost equal (or equivalent within not too large factors), \(||\xi||_1\) will be of a similar order. Moreover, \(\xi\) cannot be much smaller than its mean \(\mathbb{E} \xi\) on a large part of the probability space (where it was defined).

**Proof.** Let \(\xi\) be defined on the probability space \((\Omega, \mathcal{F}, \mathbb{P})\). By homogeneity with respect to \(\xi\), we may assume that \(\mathbb{E} \xi = 1\), so that \(dQ = \xi d\mathbb{P}\) is a probability measure. Then, (12.5) follows from the Cauchy inequality \((\mathbb{E}_Q \xi^2)^2 \leq \mathbb{E}_Q \xi^2\) on the space \((\Omega, \mathcal{F}, Q)\).

To prove (12.6), given \(r > 0\), let \(p = \mathbb{P}\{\xi \geq r\}\). By Hölder’s inequality with exponents \(3/2\) and \(3\),
\[
\mathbb{E} \xi^2 \mathbb{1}_{\{\xi \geq r\}} \leq (\mathbb{E} \xi^3)^{2/3} p^{1/3}.
\]
Hence, choosing $r = \frac{1}{\sqrt{2}} \|\xi\|_2$, we get
\[
\mathbb{E} \xi^2 = \mathbb{E} \xi^2 1_{\{\xi \geq r\}} + \mathbb{E} \xi^2 1_{\{\xi < r\}} \\
\leq (\mathbb{E} \xi^3)^{2/3} p^{1/3} + r^2 = (\mathbb{E} \xi^3)^{2/3} p^{1/3} + \frac{1}{2} \mathbb{E} \xi^2.
\]
Hence $p^{1/3} \geq \frac{1}{2(\mathbb{E} \xi^3)^{2/3}} \mathbb{E} \xi^2$ which is the desired bound (12.6). \hfill \Box

We now combine Lemma 12.2 with Lemma 12.3 which is applied on the unit sphere to $\xi(\theta) = \omega(F, F)$ viewed as a random variable on the probability space $(\mathbb{S}^{n-1}, s_{n-1})$. Note that necessarily $b \geq 1$ in the isotropic case.

**Proposition 12.4.** Let $X$ be an isotropic random vector in $\mathbb{R}^n$ such that $|X| \leq b \sqrt{n}$ a.s. Assume that
\[
\mathbb{E}_\theta \omega^2(F, F) \geq \frac{D}{n}
\]
with some $D > 0$. Then
\[
\mathbb{E}_\theta \omega(F, F) \geq \frac{c}{(1 + \sigma_4)^3 b^3} \frac{D^2}{(\log n)^{12} \sqrt{n}}. \tag{12.7}
\]
Moreover,
\[
s_{n-1}\{\omega(F, F) \geq \frac{1}{\sqrt{2n}} \sqrt{D}\} \geq \frac{c}{(1 + \sigma_4)^6 b^3} \frac{D^3}{(\log n)^{12}}.
\]

**Proof of Theorem 1.3.** The lower bound (12.7) implies a similar assertion about the Kolmogorov distance. Indeed, by Proposition 11.1 with $\alpha = 1$, we have
\[
\frac{1}{\sqrt{b}} \mathbb{E}_\theta \omega(F, F) \leq 14 (\log n)^{1/4} \mathbb{E}_\theta \rho(F, F) + \frac{8}{n^4}.
\]
Using $\frac{8}{n^4} < \frac{1}{n^3} \cdot 14 (\log n)^{1/4}$, we therefore obtain that
\[
\mathbb{E}_\theta \rho(F, F) \geq \frac{1}{14\sqrt{b} (\log n)^{1/4}} \mathbb{E}_\theta \omega(F, F) - \frac{1}{n^3}
\]
\[
\geq \frac{c}{(1 + \sigma_4)^3 b^2} \frac{D^4}{(\log n)^4 \sqrt{n}} - \frac{1}{n^3}.
\]
To replace $F$ with $\Phi$, it remains to recall the bound $\rho(F, \Phi) \leq \frac{c}{n} (1 + \sigma_4^2)$, cf. (2.3). \hfill \Box

In the isotropic case with $|X|^2 = n$ a.s., the above lower bound is further simplified to
\[
\mathbb{E}_\theta \rho(F, F) \geq \frac{cD^2}{(\log n)^{1/4} \sqrt{n}} - \frac{1}{n^3}.
\]

On the other hand, let us note that the rates for the normal approximation of $F_\theta$ that are better than $1/n$ (on average) cannot be obtained under the support assumption as above. That is, if $|X| = \sqrt{n}$ a.s., then
\[
\mathbb{E}_\theta \rho(F_\theta, \Phi) \geq \frac{c}{n}.
\]
Indeed, using the convexity of the distance function $G \to \rho(G, \Phi)$ and applying Jensen’s inequality, we have that $\mathbb{E}_\theta \rho(F_\theta, \Phi) \geq \rho(F, \Phi)$. It remains to appeal to Proposition 2.6.
13. Functional Examples

13.1. For the trigonometric system as in item (i) of the Introduction (with \( n \) even), the linear forms

\[
(X, \theta) = \sqrt{2} \sum_{k=1}^{\frac{n}{2}} (\theta_{2k-1} \cos(kt) + \theta_{2k} \sin(kt)), \quad \theta = (\theta_1, \ldots, \theta_n) \in S^{n-1},
\]

represent trigonometric polynomials of degree at most \( \frac{n}{2} \). The normalization \( \sqrt{2} \) is chosen in order to meet the requirement that the random vector \( X \) will be isotropic with respect to the normalized Lebesgue measure \( \mathbb{P} \) on \( \Omega = (-\pi, \pi) \). Moreover, in this case \( |X| = \sqrt{n} \), so that \( \sigma_4 = 0 \). Hence, by Theorem 1.1, we have the upper bounds (1.6). On the other hand, since for all \( k \leq \frac{n}{2} \)

\[
|X_k(t) - X_k(s)| \leq k \sqrt{2} |t - s| \leq \frac{n}{\sqrt{2}} |t - s|, \quad t, s \in \Omega,
\]

the Lipschitz condition (7.1) is fulfilled with \( L(t) = \frac{t}{\sqrt{2}} \). Hence, Proposition 7.1 is applicable and yields the lower bound

\[
\mathbb{E}_\theta \omega^2(F_\theta, \Phi) \geq \frac{c_1}{n} - \frac{c_2}{n^2} \geq \frac{c_3}{n},
\]

where in the last inequality we assume that \( n \geq n_0 \) for some universal integer \( n_0 \). This restriction may be dropped, since the distances \( \omega^2(F_\theta, \Phi) \) are bounded away from zero for \( n < n_0 \) uniformly over all \( \theta \in S^{n-1} \), just due to the property that the distributions \( F_\theta \) are supported on the bounded interval \([-\sqrt{n_0}, \sqrt{n_0}] \). Note that the above lower estimate (may also be obtained by applying Theorem 1.1. Thus, for all \( n \geq 2 \),

\[
\frac{c_0}{n} \leq \mathbb{E}_\theta \omega^2(F_\theta, \Phi) \leq \frac{c_1}{n}. \tag{13.1}
\]

Applying Proposition 12.4, we obtain similar equivalent bounds for the \( L^1 \)-norm (modulo logarithmic factors). Namely, it gives

\[
\frac{c_0}{(\log n)^{15} \sqrt{n}} \leq \mathbb{E}_\theta \omega(F_\theta, \Phi) \leq \frac{c_1}{\sqrt{n}}. \tag{13.2}
\]

We also get an analogous pointwise lower bound on the “essential” part of the unit sphere.

A similar statement is also true for the Kolmogorov distance. Here, the upper bound is provided in Proposition 9.1, while the lower bound is obtained when combining Theorem 1.3 with the left inequality in (13.1). That is,

\[
\frac{c_0}{(\log n)^4 \sqrt{n}} \leq \mathbb{E}_\theta \rho(F_\theta, \Phi) \leq (\mathbb{E}_\theta \rho^2(F_\theta, \Phi))^{1/2} \leq \frac{c_1 \log n}{\sqrt{n}}. \tag{13.3}
\]

13.2. Similar results remain true for the cosine trigonometric system \( X = (X_1, \ldots, X_n) \) as in item (ii). Due to the normalization \( \sqrt{2} \), the distribution of \( X \) is isotropic in \( \mathbb{R}^n \). The property \( |X| = \sqrt{n} \) is not true anymore; however, there is a pointwise bound \( |X| \leq \sqrt{2n} \). In addition, the variance functional \( \sigma_4^2 \) does not depend on \( n \). Indeed, write

\[
X_k^2 = 2 \cos^2(kt) = 1 + \cos(2kt) = 1 + \frac{e^{2ikt} + e^{-2ikt}}{2},
\]
so that
\[2 (|X|^2 - n) = \sum_{0<|k|\leq n} e^{2ikt}, \]
\[4 (|X|^2 - n)^2 = \sum_{0<|k|,|l|\leq n} e^{2i(k+l)t}. \]

It follows that
\[4 \text{Var}(|X|^2) = \sum_{0<|k|,|l|\leq n} \mathbb{E} e^{2i(k+l)t} = \sum_{0<|k|\leq n, l=-k} 1 = 2n. \]

Hence
\[\sigma_4^2 = \frac{1}{n} \text{Var}(|X|^2) = \frac{1}{2}. \]

As before, the Lipschitz condition is fulfilled with the function \(L(t) = t\sqrt{2}\). Therefore, with similar arguments we obtain all the bounds (13.1)-(13.3).

Let us also note that the sums \(\sum_{k=1}^n \cos(kt)\) remain bounded for growing \(n\) (for any fixed \(0 < t < \pi\)). Hence the normalized sums
\[S_n = \frac{1}{\sqrt{n}} \sum_{k=1}^n X_k = \frac{\sqrt{2}}{\sqrt{n}} \sum_{k=1}^n \cos(kt), \]
which correspond to \(\langle X, \theta \rangle\) with equal coefficients, are convergent to zero pointwise on \(\Omega\) as \(n \to \infty\). In particular, they fail to satisfy the central limit theorem.

13.3. An example closely related to the cosine trigonometric system is represented by the normalized Chebyshev’s polynomials \(X_k\) as in item (iii), which we consider for \(k = 1, 2, \ldots, n\). These polynomials are orthonormal on the interval \(\Omega = (-1, 1)\) with respect to the probability measure
\[\frac{dp(t)}{dt} = \frac{1}{\pi \sqrt{1-t^2}}, \quad -1 < t < 1, \]
cf. e.g. [18]. Similarly to 13.2, for the random vector \(X = (X_1, \ldots, X_n)\) we find that
\[4 (|X|^2 - n)^2 = \sum_{0<|k|,|l|\leq n} \exp\{2i(k+l) \arccos t\}. \]

It follows that
\[4 \text{Var}(|X|^2) = \sum_{0<|k|,|l|\leq n} \mathbb{E} \exp\{2i(k+l) \arccos t\} = \sum_{0<|k|\leq n} 1 = 2n, \]
so that \(\sigma_4^2 = \frac{1}{n} \text{Var}(|X|^2) = \frac{1}{2}\). In addition, for all \(k \leq n\),
\[|X_k(t) - X_k(s)| \leq k \sqrt{2} |\arccos t - \arccos s|, \quad t, s \in \Omega, \]
which implies that the Lipschitz condition is fulfilled with the function \(L(t) = \sqrt{2} \arccos t\). As a result, with similar arguments we obtain the bounds (13.1)-(13.3) as well.

13.4. Turning to item (iv), consider the functions of the form
\[X_k(t, s) = \Psi(kt + s), \]
assuming that $\Psi$ is a 1-periodic measurable function on the real line such that

$$\int_0^1 \Psi(x) \, dx = 0 \quad \text{and} \quad \int_0^1 \Psi(x)^2 \, dx = 1.$$ 

These conditions ensure that the random vector $X = (X_1, \ldots, X_n)$ is isotropic in $\mathbb{R}^n$ with respect to the Lebesgue measure $\mathbb{P}$ on the square $\Omega = (0, 1) \times (0, 1)$, with $\mathbb{E}X_k = 0$. In fact, as was emphasized in [12], \{$X_k\}_{k=1}^{\infty}$ represents a strictly stationary sequence of pairwise independent random variables on $\Omega$. The latter implies in particular that, if $\Psi$ has finite a 4-th moment on $(0, 1)$, the variance functional

$$\sigma_4^2 = \frac{1}{n} \text{Var}(|X|^2) = \int_0^1 \Psi(x)^4 \, dx - 1$$

is finite and does not dependent on $n$. Hence, by Theorem 1.1, cf. (1.6), the upper bounds in (13.1)-(13.3) hold true with a constant $c_1$ depending on the 4-th moment of $\Psi$ on $(0, 1)$.

In addition, if the function $\Psi$ has finite Lipschitz constant $\|\Psi\|_{\text{Lip}}$, then for all $(t_1, t_2)$ and $(s_1, s_2)$ in $\Omega$,

$$|X_k(t_1, t_2) - X_k(s_1, s_2)| \leq \|\Psi\|_{\text{Lip}} (k |t_1 - s_1| + |t_2 - s_2|).$$

This means that the Lipschitz condition (7.5) is fulfilled with linear functions $L_1$ and $L_2$. Hence, one may apply Proposition 7.5 giving the lower bound

$$\mathbb{E}_{\theta} \omega^2(F_\theta, F) \geq \frac{c_\Psi}{n} - \frac{c(1 + \sigma_4^4)}{n^2}$$

in full analogy with item (i). Hence $\mathbb{E}_{\theta} \omega^2(F_\theta, \Phi) \geq \frac{c_\Psi}{n}$ for all $n \geq n_0$, where the positive constants $c_\Psi$, $c_\Psi'$, and an integer $n_0 \geq 1$ depend on the distribution of $\Psi$ only. Since the collection \{$F_\theta$\} is separated from $\Phi$ in the weak sense for $n < n_0$ (by the uniform boundedness of $X_k$’s), the latter bound holds true for all $n \geq 2$. Also, as Lipschitz functions on $(0, 1)$ are bounded, we have $|X| \leq b\sqrt{n}$ with $b = \sup_x |f(x)|$, and one may apply Theorem 1.3.

Let us summarize: The upper bounds in (13.1) – (13.3) hold true, if $\Psi$ has finite 4-th moment under the uniform distribution on $(0, 1)$. The lower bounds hold under an additional assumption that $\Psi$ has a finite Lipschitz semi-norm (with constants depending on $\Psi$ only).

Choosing, for example, $\Psi(t) = \cos t$, we obtain the system $X_k(t, s) = \cos(kt + s)$, which is closely related to the cosine trigonometric system. The main difference is however the property that $X_k$’s are now pairwise independent. Nevertheless, the normalized sums $\frac{1}{\sqrt{n}} \sum_{k=1}^{n} \cos(kt + s)$ fail to satisfy the central limit theorem.

14. The Walsh System; Empirical Measures

14.1. The Walsh system on the discrete cube $\Omega = \{-1, 1\}^d$ with the uniform counting measure $\mathbb{P}$ as in item (v) in Introduction forms a complete orthonormal system in $L^2(\Omega, \mathbb{P})$. Note that each $X_\tau$ with $\tau \neq \emptyset$ is a symmetric Bernoulli random variable taking the values $-1$ and 1 with probability $\frac{1}{2}$. For simplicity, we exclude from this family the constant $X_{\emptyset} = 1$ and consider $X = \{X_\tau\}_{\tau \neq \emptyset}$ as a random vector in $\mathbb{R}^n$ of dimension $n = 2^d - 1$. As before, $F_\emptyset$ denotes the distribution function of the linear form

$$\langle X, \theta \rangle = \sum_{\tau \neq \emptyset} \theta_\tau X_\tau, \quad \theta = \{\theta_\tau\}_{\tau \neq \emptyset} \in S^{n-1}.$$
Since $|X_\tau| = 1$ and thus $|X| = \sqrt{n}$, for the study of the asymptotic behavior of the $L^2$-distance $\omega(F_\theta, \Phi)$ on average, one may apply Theorem 1.1. Let $Y$ be an independent copy of $X$, which we realize on the product space $\Omega^2 = \Omega \times \Omega$ with product measure $\mathbb{P}^2 = \mathbb{P} \times \mathbb{P}$ by

$$X_\tau(t, s) = \prod_{k \in \tau} t_k, \quad Y_\tau(t, s) = \prod_{k \in \tau} s_k \quad t = (t_1, \ldots, t_d), \quad s = (s_1, \ldots, s_d) \in \Omega.$$ 

Then the inner product

$$\langle X, Y \rangle = \sum_{\tau \neq \emptyset} X_\tau(t, s)Y_\tau(t, s) = -1 + \prod_{k=1}^d (1 + t_k s_k)$$

takes only two values, namely $2^d - 1$ in the case $t = s$, and $-1$ if $t \neq s$. Hence

$$\mathbb{E} \langle X, Y \rangle^3 = (2^d - 1)^3 2^{-d} + (1 - 2^{-d}) = \frac{n^3}{n+1} + \left(1 - \frac{1}{n+1}\right) \sim n^2$$

and

$$\mathbb{E} \langle X, Y \rangle^4 = (2^d - 1)^4 2^{-d} + (1 - 2^{-d}) = \frac{n^4}{n+1} + \left(1 - \frac{1}{n+1}\right) \sim n^3.$$ 

In other words, $m_3^2 \sim \sqrt{n}$ and $m_4^2 \sim n$ as $n \to \infty$. As a result, we may conclude that all inequalities in (13.1)-(13.3) are fulfilled for this system as well.

14.1. Here is another interesting example leading to the similar rate of normal approximation. Let $e_1, \ldots, e_n$ denote the canonical basis in $\mathbb{R}^n$. Assuming that the random vector $X = (X_1, \ldots, X_n)$ takes only $n$ values, $\sqrt{n} e_1, \ldots, \sqrt{n} e_n$, each with probability $1/n$, the linear form $\langle X, \theta \rangle$ also takes $n$ values, namely, $\sqrt{n} \theta_1, \ldots, \sqrt{n} \theta_n$, each with probability $1/n$, for any $\theta = (\theta_1, \ldots, \theta_n) \in \mathbb{S}^{n-1}$. That is, as a measure, the distribution of $\langle X, \theta \rangle$ is described as

$$F_\theta = \frac{1}{n} \sum_{k=1}^n \delta_{\sqrt{n} \theta_k},$$

which may be viewed as an empirical measure based on the observations $Z_k = \sqrt{n} \theta_k$, $k = 1, \ldots, n$. Each $Z_k$ is almost standard normal, while jointly they are nearly independent (we have already considered in detail its characteristic functions $J_n(t\sqrt{n})$).

Just taking a short break, let us recall that when $Z_k$ are indeed standard normal and independent, it is well-known that the empirical measures $G_n = \frac{1}{n} \sum_{k=1}^n \delta_{Z_k}$ approximate the standard normal law $\Phi$ with rate $1/\sqrt{n}$ with respect to the Kolmogorov distance. More precisely, $\mathbb{E} G_n = \Phi$ and there is a subgaussian deviation bound

$$\mathbb{P} \{ \sqrt{n} \rho(G_n, \Phi) \geq r \} \leq 2e^{-2r^2}, \quad r \geq 0$$

(cf. [24]). In particular, $\mathbb{E} \rho(G_n, \Phi) \leq c/\sqrt{n}$. Note that the characteristic function of $G_n$,

$$g_n(t) = \frac{1}{n} \sum_{k=1}^n e^{itZ_k},$$

has mean $g(t) = e^{-t^2/2}$ and variance

$$\mathbb{E} |g_n(t) - g(t)|^2 = \frac{1}{n} \text{Var}(e^{itZ_1}) = \frac{1}{n} (1 - |\mathbb{E} e^{itZ_1}|^2) = \frac{1}{n} (1 - e^{-t^2}).$$
Hence, applying Plancherel’s theorem and using the identity (4.7) for the functions \( \psi_t(\alpha) \) with \( r = \alpha = 0 \), we also have

\[
\mathbb{E} \omega^2(G_n, \Phi) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \mathbb{E} \left| \frac{g_n(t) - g(t)}{t} \right|^2 dt
\]

\[
= \frac{1}{2\pi n} \int_{-\infty}^{\infty} \frac{1 - e^{-t^2}}{t^2} dt = \frac{1}{n\sqrt{\pi}}.
\]

Thus, on average the \( L^2 \)-distance \( \omega(G_n, \Phi) \) is of order \( 1/\sqrt{n} \) as well.

Similar properties may be expected for the random variables \( Z_k = \sqrt{n} \theta_k \) and hence for the random vector \( X \). Note that \( |X| = \sqrt{n} \), while

\[
\mathbb{E} \langle X, \theta \rangle^2 = \frac{1}{n} \sum_{k=1}^{n} (\sqrt{n} \theta_k)^2 = 1, \quad \theta \in \mathbb{S}^{n-1},
\]

so that \( X \) is isotropic. We now involve an asymptotic formula of Corollary 5.1 which yields

\[
\mathbb{E}_\theta \omega^2(F_\theta, \Phi) = \frac{1}{\sqrt{\pi}} \left( 1 + \frac{1}{4n} \right) \mathbb{E} \left( 1 - (1 - \xi)^{1/2} \right) - \frac{1}{8n\sqrt{\pi}} + O\left( \frac{1}{n^2} \right),
\]

where \( \xi = \frac{\langle X, Y \rangle}{n} \) with \( Y \) being an independent copy of \( X \). By the definition, \( \xi \) takes only two values, 1 with probability \( \frac{1}{n} \) and 0 with probability \( 1 - \frac{1}{n} \). Hence, the last expectation is equal to \( \frac{1}{n} \), and we get

\[
\mathbb{E}_\theta \omega^2(F_\theta, \Phi) = \frac{7/8}{n\sqrt{\pi}} + O\left( \frac{1}{n^2} \right).
\]

As for the Kolmogorov distance, one may apply again Theorem 1.3, which leads to the two-sided bound (13.3). Apparently, both logarithmic terms can be removed. Their appearance here is explained by the use of Fourier tools (in the form of Berry-Esseen bounds), while the proof of the Dvoretzky-Kiefer-Wolfowitz inequality on \( \rho(G_n, \Phi) \) in [15] is based on entirely different arguments.

15. Improved Rates for Lacunary Systems

An orthonormal sequence of random variables \( \{X_k\}_{k=1}^\infty \) in \( L^2(\Omega, \mathfrak{F}, \mathbb{P}) \) is called a lacunary system of order \( p > 2 \), if for any sequence \( \{a_k\} \) in \( L^2 \), the series \( \sum_{k=1}^\infty a_k X_k \) converges in \( L^p \)-norm to an element of \( L^p(\Omega, \mathfrak{F}, \mathbb{P}) \). This property is equivalent to the validity of the Khinchine-type inequality

\[
\mathbb{E} \left| a_1 X_1 + \cdots + a_n X_n \right|^p \leq M_p \left( a_1^2 + \cdots + a_n^2 \right)^{1/2}
\]

(15.1)

for arbitrary \( a_k \in \mathbb{R} \) with some constant \( M_p \) independent of \( n \) and the choice of the coefficients \( a_k \). For basic properties of such systems we refer an interested reader to the books [18, 19].

Starting from an orthonormal lacunary system of order \( p = 4 \), consider the random vector \( X = (X_1, \ldots, X_n) \). According to Theorem 1.1, if \( |X|^2 = n \) a.s. and \( \mathbb{E} X = 0 \), then

\[
c \mathbb{E}_\theta \omega^2(F_\theta, \Phi) \leq \frac{1}{n^3} \mathbb{E} \langle X, Y \rangle^3 + \frac{1}{n^4} \mathbb{E} \langle X, Y \rangle^4,
\]

(15.2)

where \( Y \) is an independent copy of \( X \). A similar bound

\[
c \mathbb{E}_\theta \rho^2(F_\theta, \Phi) \leq \frac{\log n}{n^3} \mathbb{E} \langle X, Y \rangle^3 + \frac{(\log n)^2}{n^4} \mathbb{E} \langle X, Y \rangle^4
\]

(15.3)
also holds for the Kolmogorov distance. As easily follows from (15.1),

\[ E |\langle X, Y \rangle|^p \leq M_4^{2p} n^{p/2}. \]

In particular,

\[ E |\langle X, Y \rangle|^3 \leq M_4^6 n^{3/2}, \quad E \langle X, Y \rangle^4 \leq M_4^4 n^2. \]

Hence, the bounds (15.2)-(15.3) lead to the estimates

\[ c_\mathcal{E}_\mathcal{O} \omega^2(F_\mathcal{O}, \Phi) \leq \frac{1}{n^{3/2}} M_4^6 + \frac{1}{n^2} M_4^4, \]

\[ c_\mathcal{E}_\mathcal{O} \rho^2(F_\mathcal{O}, \Phi) \leq \frac{\log n}{n^{3/2}} M_4^6 + \frac{(\log n)^2}{n^2} M_4^4. \]

Thus, if \( M_4 \) is bounded, both distances are at most of order \( n^{-3/4} \) on average (modulo a logarithmic factor). Moreover, if

\[ \Sigma_3(n) = E \langle X, Y \rangle^3 = \sum_{1 \leq i_1, i_2, i_3 \leq n} \left( E X_{i_1} X_{i_2} X_{i_3} \right)^2 \quad (15.4) \]

is bounded by a multiple of \( n \), then these distances are on average at most \( 1/n \) (modulo a logarithmic factor in the case of \( \rho \)).

For an illustration, on the interval \( \Omega = (-\pi, \pi) \) with the uniform measure \( d\mathbb{P}(t) = \frac{1}{2\pi} dt \), consider a finite trigonometric system \( X = (X_1, \ldots, X_n) \) with components

\[ X_{2k-1}(t) = \sqrt{2} \cos(mt), \quad X_{2k}(t) = \sqrt{2} \sin(mt), \quad k = 1, \ldots, n/2, \]

where \( m_k \) are positive integers such that \( \frac{m_{k+1}}{m_k} \geq q > 1 \) (assuming that \( n \) is even). Then \( X \) is an isotropic random vector satisfying \( |X|^2 = n \) and \( E X = 0 \), and with \( M_4 \) bounded by a function of \( q \) only. For evaluation of the moment \( \Sigma_3(n) \), one may use the identities

\[ \cos t = E_\varepsilon e^{i t} = \frac{1}{n} E e^{i t}, \quad \sin t = \frac{1}{i} E_\varepsilon e^{i t}, \]

where \( \varepsilon \) is a Bernoulli random variable taking the values \( \pm 1 \) with probability \( \frac{1}{2} \). Let \( \varepsilon_1, \varepsilon_2, \varepsilon_3 \) be independent copies of \( \varepsilon \). Using the property that \( \varepsilon_1 \varepsilon_3 \) and \( \varepsilon_2 \varepsilon_3 \) are independent, the first identity implies that, for all integers \( 1 \leq n_1 \leq n_2 \leq n_3 \),

\[ E \cos(n_1 t) \cos(n_2 t) \cos(n_3 t) = E_\varepsilon \exp\{i(\varepsilon_1 n_1 + \varepsilon_2 n_2 + \varepsilon_3 n_3)\} \]

\[ = E_\varepsilon I\{\varepsilon_1 n_1 + \varepsilon_2 n_2 + \varepsilon_3 n_3 = 0\} \]

\[ = E_\varepsilon I\{\varepsilon_1 n_1 + \varepsilon_2 n_2 + \varepsilon_3 n_3 = n_3\} = \frac{1}{4} I\{n_1 + n_2 = n_3\}, \]

where where \( E_\varepsilon \) means the expectation over \( \{\varepsilon_1, \varepsilon_2, \varepsilon_3\} \), and where \( I\{A\} \) denotes the indicator of the event \( A \). Similarly, involving also the identity for the sine function, we have

\[ E \sin(n_1 t) \sin(n_2 t) \cos(n_3 t) = -E_\varepsilon \exp\{i(\varepsilon_1 n_1 + \varepsilon_2 n_2 + \varepsilon_3 n_3)\} \]

\[ = -E_\varepsilon \exp\{i(\varepsilon_1 n_1 + \varepsilon_2 n_2 + \varepsilon_3 n_3) = 0\} \]

\[ = -E_\varepsilon \exp\{i(\varepsilon_1 n_1 + \varepsilon_2 n_2 + \varepsilon_3 n_3 = n_3\} = -\frac{1}{4} I\{n_1 + n_2 = n_3\}, \]

\[ E \sin(n_1 t) \cos(n_2 t) \sin(n_3 t) = -E_\varepsilon \exp\{i(\varepsilon_1 n_1 + \varepsilon_2 n_2 + \varepsilon_3 n_3)\} \]

\[ = -E_\varepsilon \exp\{i(\varepsilon_1 n_1 + \varepsilon_2 n_2 + \varepsilon_3 n_3 = 0\} \]

\[ = -E_\varepsilon \exp\{i(\varepsilon_1 n_1 + \varepsilon_2 n_2 + \varepsilon_3 n_3 = n_3\} = -\frac{1}{4} I\{n_1 + n_2 = n_3\}, \]
\[ \mathbb{E} \cos(n_1 t) \sin(n_2 t) \sin(n_3 t) = -\mathbb{E}_\varepsilon \mathbb{E}_\varepsilon \varepsilon_3 \exp\{i(\varepsilon_1 n_1 + \varepsilon_2 n_2 + \varepsilon_3 n_3) t\} \]
\[ = -\mathbb{E}_\varepsilon \varepsilon_2 \varepsilon_3 I\{\varepsilon_1 n_1 + \varepsilon_2 n_2 + \varepsilon_3 n_3 = 0\} \]
\[ = -\mathbb{E}_\varepsilon \varepsilon_2 I\{\varepsilon_1 n_1 + \varepsilon_2 n_2 = n_3\} = -\frac{1}{4} I\{n_1 + n_2 = n_3\}. \]

On the other hand, if the sine function appears in the product once or three times, such expectations will be vanishing. They are thus vanishing in all cases where \( n_1 + n_2 \neq n_3 \), and do not exceed \( \frac{1}{4} \) in absolute value for any combination of sine and cosine terms in all cases with \( n_1 + n_2 = n_3 \). Therefore, the moment \( \Sigma_3(n) \) in (15.4) is bounded by \( \frac{3}{4} 2^{3/2} T_3(n) \) where
\[ T_3(n) = \text{card}\{(i_1, i_2, i_3): 1 \leq i_1 \leq i_2 < i_3 \leq n, \ m_{i_1} + m_{i_2} = m_{i_3}\}. \]

One can now involve the lacunary assumption. If \( q \geq 2 \), the property \( 1 \leq i_1 \leq i_2 < i_3 \leq n \) implies \( m_{i_1} + m_{i_2} < m_{i_3} \), so that \( T_3(n) = \Sigma_3(n) = 0 \). In the case \( 1 < q < 2 \), define \( A_q \) to be the (finite) collection of all couples \((k_1, k_2)\) of positive integers such that
\[ q^{-k_1} + q^{-k_2} \geq 1. \]

By the lacunary assumption, if \( 1 \leq i_1 \leq i_2 < i_3 \leq n \), we have
\[ m_{i_1} + m_{i_2} \leq (q^{-(i_3-i_1)} + q^{-(i_3-i_2)}) m_{i_3} < m_{i_3}, \]
as long as the couple \((i_3 - i_1, i_2 - i_1)\) is not in \( A_q \). Hence,
\[ T_3(n) \leq \text{card}\{(i_1, i_2, i_3): 1 \leq i_1 \leq i_2 < i_3 \leq n, \ (i_3 - i_1, i_2 - i_1) \in A_q\} \]
\[ \leq n \text{card}(A_q) \leq c_q n \]
with constant depending on \( q \) only. Returning to (15.2)-(15.3), we then obtain:

**Proposition 15.1.** For the lacunary trigonometric system \( X \) of an even length \( n \) and with parameter \( q > 1 \), we have
\[ \mathbb{E}_\theta \omega^2(F_\theta, \Phi) \leq c_q \frac{n^2}{n^2}, \quad \mathbb{E}_\theta \rho^2(F_\theta, \Phi) \leq c_q \frac{(\log n)^2}{n^2}, \]
where the constants \( c_q \) depend \( q \) only.

In this connection one should mention a classical result of Salem and Zygmund concerning distributions of the lacunary sums
\[ S_n = \sum_{k=1}^{n} (a_k \cos(m_k t) + b_k \sin(m_k t)) \]
with an arbitrary prescribed sequence of the coefficients \((a_k)_{k \geq 1}\) and \((b_k)_{k \geq 1}\). Assume that \( \frac{m_{k+1}}{m_k} \geq q > 1 \) for all \( k \) and put
\[ v_n^2 = \frac{1}{2} \sum_{k=1}^{n} (a_k^2 + b_k^2) \quad (v_n \geq 0), \]
so that the normalized sums \( Z_n = S_n/v_n \) have mean zero and variance one under the measure \( \mathbb{P} \). It was shown in [27] that \( Z_n \) are weakly convergent to the standard normal law, i.e., their distributions \( F_n \) under \( \mathbb{P} \) satisfy \( \rho(F_n, \Phi) \to 0 \) as \( n \to \infty \), if and only if \( \frac{a_k^2 + b_k^2}{v_n^2} \to 0 \) (in fact, the weak convergence was established on every subset of \( \Omega \) of positive measure).

Restricting to the coefficients \( \theta_{2k-1} = a_k/v_n, \theta_{2k} = b_k/v_n \), Salem-Zygmund’s theorem may be stated as the assertion that \( \rho(F_\theta, \Phi) \) is small, if and only if \( ||\theta||_\infty = \max_{1 \leq k \leq n} |\theta_k| \) is
small. The latter condition naturally appears in the central limit theorem for weighted sums of independent identically distributed random variables. Thus, Corollary 14.1 complements this result in terms of the rate of convergence in the mean on the unit sphere.

The result of [27] was generalized in [28]; it turns out there is no need to assume that all \( m_k \) are integers, and the asymptotic normality is preserved for real \( m_k \) such that \( \inf_k \frac{m_k+1}{m_k} > 1 \). However, in this more general situation, the rate \( 1/n \) as in Proposition 15.1 is no longer true (although the rate \( 1/\sqrt{n} \) is valid). The main reason is that the means
\[
E X_{2k-1} = \sqrt{2} E \cos(m_k t) = 2\sqrt{2} \frac{\sin(\pi m_k)}{\pi m_k}
\]
are non-zero anymore. For example, choosing \( m_k = 2^k + \frac{1}{2} \), we have
\[
E X_{2k-1} = \frac{4\sqrt{2}}{\pi (2^{k+1} + 1)}.
\]
Hence
\[
E \langle X, Y \rangle = |E X|^2 = \frac{32}{\pi^2} \sum_{k=1}^{n} \frac{1}{(2^{k+1} + 1)^2} \to c \quad (n \to \infty)
\]
for some absolute constant \( c > 0 \) (where \( Y \) is an independent copy of \( X \)). It can easily be seen that
\[
E \langle X, Y \rangle^2 = n + O(1), \quad E \langle X, Y \rangle^3 = O(n), \quad E \langle X, Y \rangle^4 = O(n^2).
\]
Putting \( \xi = \frac{\langle X, Y \rangle}{n} \) and applying Corollary 5.1, we find that
\[
\sqrt{\pi} E_{\theta} \omega^2(F_{\theta}, F) = \left( 1 + \frac{1}{4n} \right) E \left( 1 - (1 - \xi)^{1/2} \right) - \frac{1}{8n} + O\left( \frac{1}{n^2} \right)
\]
\[
= \left( 1 + \frac{1}{4n} \right) \left( \frac{1}{2} E\xi + \frac{1}{8} E\xi^2 \right) - \frac{1}{8n} + O\left( \frac{1}{n^2} \right)
\]
\[
= \frac{c}{2n} + O\left( \frac{1}{n^2} \right).
\]
A similar asymptotic holds as well when \( F \) is replaced with \( \Phi \).

16. Improved Rates for Independent and Log-concave Summands

Let \( X = (X_1, \ldots, X_n) \) be an isotropic random vector in \( \mathbb{R}^n \) with mean zero. If the components \( X_k \) are independent, the normal approximation for the distributions \( F_{\theta} \) of the weighted sums
\[
S_{\theta} = \theta_1 X_1 + \cdots + \theta_n X_n, \quad \theta \in \mathbb{S}^{n-1},
\]
may be controlled by virtue of the Berry-Esseen theorem under the 3-rd moment assumption. Namely, this theorem provides an upper bound
\[
\rho(F_{\theta}, \Phi) \leq c \sum_{i=1}^{n} |\theta_i|^3 E |X_i|^3
\]
(cf. e.g. [25], [26]). Since \( E |X_i|^3 \geq 1 \), the sum in (16.1) is at least \( 1/\sqrt{n} \). On the other hand, (16.1) yields an upper estimate on average
\[
E_{\theta} \rho(F_{\theta}, \Phi) \leq \frac{c \beta_3}{\sqrt{n}}, \quad \beta_3 = \max_{1 \leq i \leq n} E |X_i|^3,
\]
which is consistent with the standard rate.
As it turns out, the relations (16.1)-(16.2) are far from being optimal for most of $\theta$, as the following statement due to Klartag and Sodin shows.

**Theorem 16.1** ([21]). If the random variables $X_1, \ldots, X_n$ are independent, have mean zero, variance one, and finite 4-th moments, then

$$
\mathbb{E}_\theta \rho(F_\theta, \Phi) \leq \frac{c\beta_4}{n}, \quad \beta_4 = \frac{1}{n} \sum_{i=1}^{n} \mathbb{E}X_i^4.
$$

(16.3)

Moreover, for any $r \geq 0$,

$$
\mathbb{g}_{n-1}\left\{n^2 \rho(F_\theta, \Phi) \geq c\beta_4 r\right\} \leq 2 e^{-\sqrt{r}}.
$$

In the i.i.d. case, $\beta_4 = \mathbb{E}X_1^4$, and we obtain an upper bound of order at most $1/n$.

In fact, in the symmetric i.i.d. case, the relation (16.3) may be further sharpened under the 5-th moment assumption.

**Theorem 16.2.** If the random variables $X_1, \ldots, X_n$ are independent, identically distributed, with $\mathbb{E}X_1 = \mathbb{E}X_1^3 = 0$, $\mathbb{E}X_1^2 = 1$, and with finite moment $\beta_5 = \mathbb{E}|X|^5$, then

$$
\mathbb{E}_\theta \rho(F_\theta, \Phi) \leq \frac{c\beta_5}{n^{3/2}}.
$$

(16.4)

Moreover, for any $r \geq 0$,

$$
\mathbb{g}_{n-1}\left\{n^{3/2} \rho(F_\theta, \Phi) \geq c\beta_4 r\right\} \leq 2 \exp\{-r^{2/5}\}.
$$

We refer an interested reader to [5] and [11]. In the i.i.d. case, both inequalities (16.3) and (16.4) are sharp in the following sense. If $\alpha_3 = \mathbb{E}X_1^3 \neq 0$ and $\beta_4 < \infty$, then, for any function $G$ of bounded total variation, such that $G(\mathbb{R}) = 0$ and $G(\mathbb{R}) = 1$, we have

$$
\mathbb{E}_\theta \rho(F_\theta, G) \geq \frac{c}{n}
$$

with a constant $c > 0$ depending on $\alpha_3$ and $\beta_4$ only. Similarly, if $\alpha_3 = 0$, $\beta_4 \neq 3$, $\beta_5 < \infty$, then

$$
\mathbb{E}_\theta \rho(F_\theta, G) \geq \frac{c}{n^{3/2}},
$$

where the constant $c > 0$ depends on $\beta_4$ and $\beta_5$ only.

In the upper bounds such as (16.3), the independence assumption may be replaced with closely related hypotheses. The random vector $X$ is said to have a log-concave distribution, when it has a density of the form $p(x) = e^{-V(x)}$ where $V : \mathbb{R}^n \to (-\infty, \infty]$ is a convex function. Recall that a distribution of $X$ is coordinatewise symmetric, if $p(\varepsilon_1 x_1, \ldots, \varepsilon_n x_n) = p(x_1, \ldots, x_n)$, $x_i \in \mathbb{R}$, for any choice of signs $\varepsilon_i = \pm 1$. The following theorem sharpening (16.1) is due to Klartag.

**Theorem 16.3** ([20]). Suppose that the isotropic random vector $X = (X_1, \ldots, X_n)$ in $\mathbb{R}^n$ has a coordinatewise symmetric log-concave distribution. For all $\theta = (\theta_1, \ldots, \theta_n) \in S^{n-1}$, we have

$$
\|F_\theta - \Phi\|_{TV} \leq c \sum_{i=1}^{n} \theta_i^4.
$$

(16.5)
Here, the total variation distance is understood in the usual sense and may be defined as
\[
\|F_\theta - \Phi\|_{TV} = \int_{-\infty}^{\infty} |p_\theta(x) - \varphi(x)| \, dx,
\]
where \(p_\theta\) denotes the density of \(S_\theta\). By the assumptions, \(p_\theta\) is symmetric about the origin and is log-concave for any \(\theta \in S^{n-1}\). Note that, by the coordinatewise symmetry, the isotropy assumption is reduced to the moment condition \(\mathbb{E}X_i^2 = 1 \ (1 \leq i \leq n)\).

In particular, it follows from (16.5) that
\[
\mathbb{E}_\theta \rho(F_\theta, \Phi) \leq \mathbb{E}_\theta \|F_\theta - \Phi\|_{TV} \leq \frac{c}{n}.
\]  
(16.6)

17. Improved Rates Under Correlation-Type Conditions

Up to a logarithmically growing term, the improved rate as in the upper bound (16.3) can be achieved under more flexible correlation-type conditions (in comparison with independence). For example, one may consider an optimal value \(\Lambda = \Lambda(X)\) in the relation
\[
\text{Var}\left(\sum_{i,j=1}^{n} a_{ij} X_i X_j\right) \leq \Lambda \sum_{i,j=1}^{n} a_{ij}^2 \quad (a_{ij} \in \mathbb{R}),
\]  
(17.1)

which we called that the random vector \(X = (X_1, \ldots, X_n)\) satisfies a second order correlation condition with constant \(\Lambda\).

This quantity is finite as long as the moment \(\mathbb{E}|X|^4\) is finite. To relate \(\Lambda\) to the moment-type characteristics which we discussed before, one may apply (17.1) with equal coefficients, or (as another option) with \(a_{ij} = \theta_i \theta_j, \ \theta = (\theta_1, \ldots, \theta_n) \in S^{n-1}\). This gives that
\[
\sigma_4^2 \leq \Lambda, \quad m_4^2 \leq \sup_{\theta \in S^{n-1}} \mathbb{E}S_\theta^4 \leq 1 + \Lambda,
\]
where in the last inequality we should assume that \(\mathbb{E}S_\theta^2 = 1\) for all \(\theta\) (i.e. \(X\) is isotropic). In the latter case, necessarily \(\Lambda \geq \frac{n-1}{n}\), so that \(\Lambda\) is bounded away from zero.

If the distribution of \(X\) is “regular” in some sense, one may also bound \(\Lambda\) from above. For example, this is the case when it shares a Poincaré-type inequality
\[
\lambda_1 \text{Var}(u(X)) \leq \mathbb{E} |\nabla u(X)|^2,
\]  
(17.2)

which is required to hold in the class of all bounded, smooth functions \(u\) on \(\mathbb{R}^n\) with a constant \(\lambda_1 > 0\) independent of \(u\) (called the spectral gap). We then have
\[
\Lambda \leq \frac{4}{\lambda_1^2}, \quad \Lambda \leq \frac{4}{\lambda_1},
\]  
(17.3)

where in the second inequality we assume that \(X\) is isotropic.

The following relation is established in [9].

**Theorem 17.1.** If the distribution of \(X\) is isotropic and symmetric about the origin, then
\[
\mathbb{E}_\theta \rho(F_\theta, \Phi) \leq c\Lambda \frac{\log n}{n}.
\]  
(17.4)
The proof is based on the second order spherical concentration phenomenon which was developed in [6] with the aim of applications to randomized central limit theorems. It indicates that the deviations of any smooth function \( u(\theta) \) on \( S^{n-1} \) from the mean \( \mathbb{E}_{\theta} u(\theta) \) are at most of the order \( 1/n \), provided that \( u \) is orthogonal in \( L^2(\mathbb{R}^n, s_{n-1}) \) to all linear functions and has a “bounded” Hessian (the matrix of second order partial derivatives). Being applied to the characteristic functions \( u(\theta) = f_\theta(t) \), this property yields an upper bound

\[
\mathbb{E}_{\theta} |f_\theta(t) - f(t)|^2 \leq c\Lambda t^4 \frac{1}{n^2}
\]

on every interval \( |t| \leq An^{1/5} \) with constants \( c > 0 \) depending on the parameter \( A \geq 1 \) only. This estimate can be used to bound the integrals in (8.4), cf. Lemma 8.2, and then, recalling the second bound in (2.3) from Corollary 2.2, we arrive at

\[
(\mathbb{E}_{\theta} \rho^2(F_\theta, \Phi))^{1/2} \leq c\Lambda \log n \frac{\log n}{n}.
\]

This inequality slightly sharpens the bound (17.4).

The symmetry hypothesis in Proposition 17.1 may be dropped, if \( \Lambda \) is replaced by \( \lambda_1^{-1} \) which is a larger quantity according to (17.3). In addition, one can control large deviations of the distance \( \rho(F_\theta, \Phi) \) for most of the directions \( \theta \) (rather than on average). The corresponding assertions are obtained in [10].

**Theorem 17.2.** Let \( X \) be an isotropic random vector in \( \mathbb{R}^n \) with mean zero and a positive Poincaré constant \( \lambda_1 \). Then

\[
\mathbb{E}_{\theta} \rho(F_\theta, \Phi) \leq c\lambda_1^{-1} \frac{\log n}{n}.
\]

Moreover, for all \( r > 0 \),

\[
\mathbb{P}_{n-1}\{ \rho(F_\theta, \Phi) \geq c\lambda_1^{-1} \frac{\log n}{n} r \} \leq 2e^{-\sqrt{r}}.
\]

The logarithmic term in (17.5) may be removed using the less sensitive \( L^2 \)-distance:

\[
\mathbb{E}_{\theta} \omega^2(F_\theta, \Phi) \leq c\frac{1}{\lambda_1^2 n^2}.
\]

There is an extensive literature devoted to bounding the spectral gap \( \lambda_1 \) from below. In particular, it is positive for any log-concave probability distribution on \( \mathbb{R}^n \). A well-known conjecture raised by Kannan, Lovász and Simonovits asserts that \( \lambda_1 \) is actually bounded away from zero, as long as the random vector \( X \) has an isotropic log-concave distribution (cf. [17]). The best known dimensional lower bound up to date is due to Y. Chen [14] who showed that (for large \( n \))

\[
\lambda_1 \geq \frac{1}{n^{\varepsilon_n}}, \quad \varepsilon_n = c\left( \frac{\log \log n}{\log n} \right)^{1/2}.
\]

Applying this bound in Theorem 17.2, we therefore obtain:

**Corollary 17.3.** Let \( X \) be an isotropic random vector in \( \mathbb{R}^n \) with mean zero and a log-concave probability distribution. Then

\[
\mathbb{E}_{\theta} \rho(F_\theta, \Phi) \leq \frac{c}{n^{1-\varepsilon_n}}.
\]
Thus, there is a certain extension of Klartag’s bound (16.6) at the expense of a factor of the order $n^{\varepsilon n}$ to the entire class of isotropic log-concave probability distributions on $\mathbb{R}^n$.

In fact, one may argue in the opposite direction. For example, upper bounds of the form

$$\mathbb{E}_\theta \rho(F_{\theta}, \Phi) \leq \frac{c(\log n)^{\beta}}{n}, \quad \beta > 0,$$

in the class of log-concave probability distributions on $\mathbb{R}^n$ imply lower bounds $\lambda_1 \geq c (\log n)^{-\beta'}$ with some $\beta' > 0$, cf. [9].

References


