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# REPRESENTATION OF DISTRIBUTIONALLY ROBUST CHANCE-CONSTRAINTS

JEAN B. LASSERRE AND TILLMANN WEISSER

ABSTRACT. Given  $\mathbf{X} \subset \mathbb{R}^n$ ,  $\varepsilon \in (0, 1)$ , a parametrized family of probability distributions  $(\mu_{\mathbf{a}})_{\mathbf{a} \in \mathbf{A}}$  on  $\Omega \subset \mathbb{R}^p$ , we consider the feasible set  $\mathbf{X}_\varepsilon^* \subset \mathbf{X}$  associated with the *distributionally robust* chance-constraint

$$\mathbf{X}_\varepsilon^* = \{\mathbf{x} \in \mathbf{X} : \text{Prob}_\mu[f(\mathbf{x}, \omega) > 0] > 1 - \varepsilon, \forall \mu \in \mathcal{M}_{\mathbf{a}}\},$$

where  $\mathcal{M}_{\mathbf{a}}$  is the set of all possible mixtures of distributions  $\mu_{\mathbf{a}}$ ,  $\mathbf{a} \in \mathbf{A}$ . For instance and typically, the family  $\mathcal{M}_{\mathbf{a}}$  is the set of all mixtures of Gaussian distributions on  $\mathbb{R}$  with mean and standard deviation  $\mathbf{a} = (a, \sigma)$  in some compact set  $\mathbf{A} \subset \mathbb{R}^2$ . We provide a sequence of inner approximations  $\mathbf{X}_\varepsilon^d = \{\mathbf{x} \in \mathbf{X} : w_d(\mathbf{x}) < \varepsilon\}$ ,  $d \in \mathbb{N}$ , where  $w_d$  is a polynomial of degree  $d$  whose vector of coefficients is an optimal solution of a semidefinite program. The size of the latter increases with the degree  $d$ . We also obtain the strong and highly desirable asymptotic guarantee that  $\lambda(\mathbf{X}_\varepsilon^* \setminus \mathbf{X}_\varepsilon^d) \rightarrow 0$  as  $d$  increases, where  $\lambda$  is the Lebesgue measure on  $\mathbf{X}$ . Same results are also obtained for the more intricate case of distributionally robust “joint” chance-constraints.

## 1. INTRODUCTION

**Motivation.** In many optimization and control problems the uncertainty is often modeled by a noise  $\omega \in \Omega \subset \mathbb{R}^p$  (following some probability distribution  $\mu$ ), which interacts with the decision variable of interest<sup>1</sup>  $\mathbf{x} \in \mathbf{X} \subset \mathbb{R}^n$  via some feasibility constraint of the form  $f(\mathbf{x}, \omega) > 0$  for some function  $f : \mathbf{X} \rightarrow \mathbb{R}$ . In the *robust* approach one imposes the constraint  $\mathbf{x} \in \mathbf{X}^R := \{\mathbf{x} \in \mathbf{X} : f(\mathbf{x}, \omega) > 0, \forall \omega \in \Omega\}$  on the decision variable  $\mathbf{x}$ . However, sometimes the resulting set  $\mathbf{X}^R$  of robust decisions can be quite small or even empty.

On the other hand, if one knows the probability distribution  $\mu$  of the noise  $\omega \in \Omega$ , then a more appealing *probabilistic* approach is to tolerate a violation of the feasibility constraint  $f(\mathbf{x}, \omega) > 0$ , provided that this violation occurs with small probability  $\varepsilon > 0$ , fixed *à priori*. That is, one imposes the less conservative chance-constraint  $\text{Prob}_\mu(f(\mathbf{x}, \omega) > 0) > 1 - \varepsilon$ , which results in the larger “feasible set” of decisions

$$(1.1) \quad \mathbf{X}_\varepsilon^\mu := \{\mathbf{x} \in \mathbf{X} : \text{Prob}_\mu(f(\mathbf{x}, \omega) > 0) > 1 - \varepsilon\}.$$

In both the robust and probabilistic cases, handling  $\mathbf{X}^R$  or  $\mathbf{X}_\varepsilon^\mu$  can be quite challenging and one is interested in respective approximations that are easier to handle. There is a rich literature on chance-constrained programming since Charnes

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<sup>1</sup>As quoted from R. Henrion, *the biggest challenge from the algorithmic and theoretical points of view arise in chance constraints where the random and decision variables cannot be decoupled*. <https://www.stoprog.org/what-stochastic-programming>

and Cooper [8], Miller [29], and the interested reader is referred to Henrion [12], Dabbene [5], Li et al. [28], Prékopa [32] and Shapiro [34] for a general overview of chance constraints in optimization and control. Of particular interest are uncertainty models and methods that allow to define tractable approximations of  $\mathbf{X}_\varepsilon^\mu$ . Therefore an important issue is to analyze under which conditions on  $f$ ,  $\mu$  and the threshold  $\varepsilon$ , the resulting chance constraint (1.1) defines a convex set  $\mathbf{X}_\varepsilon^\mu$ ; see e.g. Henrion and Strugarek [13], van Ackooij [1], Nemirovski and Shapiro [31], Wang et al. [35], and the recent work of van Ackooij and Malick [2]. For instance, in [2] the authors consider joint chance-constraint ( $f(\mathbf{x}, \omega) \in \mathbb{R}^k$ ) and show that  $\mathbf{X}_\varepsilon^\mu$  is convex for sufficiently small  $\varepsilon$  if  $\omega$  is an elliptical random vector and  $f$  is convex in  $\mathbf{x}$ . A different approach to model chance constraints was considered by the first author in [20]. It uses the general Moment-SOS methodology described in [23]. Related earlier work by Jasour et al. [17] have also used this Moment-SOS approach to solve some control problems with probabilistic constraints.

However, one well-sounded critic to these probabilistic approaches is that it relies on the knowledge of the exact distribution  $\mu$  of the noise  $\omega$ , which in many cases may not be a realistic assumption. Therefore modeling the uncertainty via a single *known* probability distribution  $\mu$  is questionable, and may render the chance-constraint  $\text{Prob}_\mu(f(\mathbf{x}, \omega) > 0) > 1 - \varepsilon$  in (1.4) counter-productive. It would rather make sense to assume a *partial knowledge* on the *unknown* distribution  $\mu$  of the noise  $\omega \in \Omega$ .

To overcome this drawback, *distributionally robust* chance-constrained problems consider probabilistic constraints that must hold for a whole family of distributions and typically the family is characterized by the support and first and second-order moments; see for instance Delage and Ye [9], and Erdogan and Iyengar [11]. For instance Calafiore and El Ghaoui [6] have shown that when  $f$  is bilinear then a tractable characterization via second-order cone constraints is possible. Recently Yang and Xu [40] have considered non linear optimization problems where the constraint functions are concave in the decision variables and quasi-convex in the uncertain parameters. They show that such problems are tractable if the uncertainty is characterized by its mean and variance only; in the same spirit see also Chao Duan et al. [7], Xie and Ahmed [39] and Zhang et al. [41] for other tractable formulations of distributionally robust chance-constrained for optimal power flow problems.

**The uncertainty framework.** We also consider a framework where only partial knowledge of the uncertainty is available. But instead of assuming knowledge of some moments like in e.g. [40], we assume that typically the distribution  $\mu$  can be *any mixture* of probability distributions  $\mu_{\mathbf{a}} \in \mathcal{P}(\Omega)$  for some family  $\{\mu_{\mathbf{a}}\}_{\mathbf{a} \in \mathbf{A}} \subset \mathcal{P}(\Omega)$  that depend on a parameter vector  $\mathbf{a} \in \mathbf{A} \subset \mathbb{R}^t$ . That is:

$$\mu(B) = \int_{\mathbf{A}} \mu_{\mathbf{a}}(B) d\varphi(\mathbf{a}), \quad \forall B \in \mathcal{B}(\Omega),$$

where  $\varphi \in \mathcal{P}(\mathbf{A})$  can be any probability distribution on  $\mathbf{A}$ . For instance, if  $d\mu_{\mathbf{a}}(\omega) = u(\omega, \mathbf{a})$  for some density  $u$ , then by Fubini-Tonelli's Theorem [10, Theorem p. 85], the above measure  $\mu$  is well-defined.

Notice that in this framework *no* mean, variance or higher order moments have to be estimated. Hence it can be viewed as an alternative and/or a complement to those considered in e.g. [9, 6, 11, 40] when a good estimation of such moments is

not possible. Indeed in many cases, providing a box (where the mean vector can lie) and a possible range  $\underline{\delta} \mathbf{I} \preceq \Sigma \preceq \bar{\delta} \mathbf{I}$  for the covariance matrix  $\Sigma$ , can be more realistic than providing a single mean vector and a single covariance matrix. Below are some examples of possible mixtures.

**Example 1.1** (Mixture of Gaussian's).  $\Omega = \mathbb{R}$ ,  $\mathbf{a} = (a, \sigma) \in \mathbf{A} := [\underline{a}, \bar{a}] \times [\underline{\sigma}, \bar{\sigma}] \subset \mathbb{R}^2$ , with  $\underline{\sigma} > 0$ , and

$$d\mu_{\mathbf{a}}(\omega) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(\omega - a)^2}{2\sigma^2}\right) d\omega,$$

that is  $\mu_{\mathbf{a}}$  is a mixture of Gaussian probability measures with mean-deviation couple  $(a, \sigma) \in \mathbf{A}$ .

**Example 1.2** (Mixture of Exponential's).  $\Omega = \mathbb{R}_+$ ,  $\mathbf{a} = a \in \mathbf{A} := [\underline{a}, \bar{a}] \subset \mathbb{R}$  with  $\underline{a} > 0$ , and

$$d\mu_{\mathbf{a}}(\omega) = \frac{1}{a} \exp(-\omega/a) d\omega,$$

that is,  $\mu_{\mathbf{a}}$  is a mixture of exponential probability measures with parameter  $1/a$ ,  $a \in \mathbf{A}$ .

**Example 1.3** (Mixture of elliptical's). In [2] the authors have considered chance-constraints for the class of elliptical random vectors. In our framework and in the univariate case,  $\Omega = \mathbb{R}$ ,  $\mathbf{a} = (a, \sigma) \in \mathbf{A} := [\underline{a}, \bar{a}] \times [\underline{\sigma}, \bar{\sigma}] \subset \mathbb{R}^2$ , with  $\underline{\sigma} > 0$ . Let  $\theta : \mathbb{R}^+ \rightarrow \mathbb{R}$  be such that  $\int_0^\infty t^k d\theta(t) < \infty$  for all  $k$ , and let  $p = \int_{\mathbb{R}} \theta(t^2) dt$ . Then:

$$d\mu_{\mathbf{a}}(\omega) = \frac{1}{p\sigma} \theta\left(\frac{(\omega - a)^2}{\sigma^2}\right) d\omega, \quad \mathbf{a} \in \mathbf{A}.$$

**Example 1.4** (Mixture of Poisson's).  $\Omega = \mathbb{N}$  and  $\mathbf{a} = a \in \mathbf{A} := [\underline{a}, \bar{a}] \subset \mathbb{R}$  with  $\underline{a} > 0$ , and

$$\mu_{\mathbf{a}}(k) = \exp(-a) \frac{a^k}{k!}, \quad k = 0, 1, \dots; \quad \mathbf{a} \in \mathbf{A},$$

that is,  $\mu_{\mathbf{a}}$  is a mixture of Poisson probability measures with parameter  $a \in \mathbf{A}$ .

**Example 1.5** (Mixture of Binomial's). Let  $\Omega = \{0, 1, \dots, N\}$  and  $\mathbf{a} = a \in \mathbf{A} := [\underline{a}, \bar{a}] \subset [0, 1]$ , and

$$\mu_{\mathbf{a}}(k) = \binom{N}{k} a^k (1-a)^{N-k}, \quad k = 0, 1, \dots, N.$$

**Example 1.6.** With  $\Omega = \mathbb{R}$  one is given a finite family of probability measures  $(\mu_i)_{i=1, \dots, p} \subset \mathcal{P}(\Omega)$ . Then  $\mathbf{a} = a \in \mathbf{A} := \{1, \dots, p\} \subset \mathbb{R}$ , and

$$d\mu(\omega) = \sum_{a=1}^p \lambda_a d\mu_a(\omega); \quad \sum_{a \in \mathbf{A}} \lambda_a = 1; \quad \lambda_a \geq 0,$$

that is,  $\mu_{\mathbf{a}}$  is a finite convex combination of the probability measures  $(\mu_{\mathbf{a}})$ .

In this new uncertainty framework one now has to consider the set:

$$(1.2) \quad \mathcal{M}_{\mathbf{a}} := \left\{ \int_{\mathbf{A}} d\mu_{\mathbf{a}}(\omega) \varphi(d\mathbf{a}) : \varphi \in \mathcal{P}(\mathbf{A}) \right\},$$

where  $\mathcal{P}(\mathbf{A})$  is the set of probability measures on  $\mathbf{A}$ , and in a *distributionally robust chance-constraint approach*, with  $\varepsilon > 0$  fixed, one considers the set:

$$(1.3) \quad \mathbf{X}_{\varepsilon}^* := \{ \mathbf{x} \in \mathbf{X} : \text{Prob}_{\mu}(f(\mathbf{x}, \omega) > 0) > 1 - \varepsilon, \quad \forall \mu \in \mathcal{M}_{\mathbf{a}} \},$$

as new feasible set of decision variables. In general  $\mathbf{X}_\varepsilon^*$  is non-convex and can even be disconnected. Therefore obtaining accurate approximations of  $\mathbf{X}_\varepsilon^*$  is a difficult challenge. Our ultimate goal is to replace optimization problems in the general form:

$$(1.4) \quad \min_{\mathbf{x}} \{ u(\mathbf{x}) : \mathbf{x} \in C \cap \mathbf{X}_\varepsilon^* \},$$

(where  $u$  is a polynomial) with

$$(1.5) \quad \min_{\mathbf{x}} \{ u(\mathbf{x}) : \mathbf{x} \in C \cap W \geq 0 \},$$

where the uncertain parameter  $\omega$  has disappeared from the description of a suitable inner approximation  $W$  of  $\mathbf{X}_\varepsilon^*$ , with  $W := \{ \mathbf{x} \in \mathbf{X} : w(\mathbf{x}) \leq 0 \}$  for some polynomial  $w$ . So if  $C$  is a basic semi-algebraic set then (1.5) is a standard polynomial optimization problem. Of course the resulting optimization problem (1.5) may still be hard to solve because the set  $C \cap W$  is not convex in general. But this may be the price to pay for avoiding a too conservative formulation of the problem. However, since in the formulation (1.5) one has got rid of the disturbance parameter  $\omega$ , one may then apply the arsenal of Non Linear Programming algorithms to get a local minimizer of (1.5). If  $n$  is not too large or if some sparsity is present in problem (1.5) one may even run a hierarchy of semidefinite relaxations to approximate its global optimal value; for more details on the latter, the interested reader is referred to [23].

**Contribution.** We consider approximating  $\mathbf{X}_\varepsilon^*$  as a challenging mathematical problem and explore whether it is possible to solve it under minimal assumptions on  $f$  and/or  $\mathcal{M}_a$ . Thus the focus is more on the existence and definition of a prototype “algorithm” (or approximation scheme) rather than on its “scalability”. Of course the latter issue of scalability is important for practical applications and we hope that the present contribution will provide insights on how to develop more “tractable” (but so more conservative) versions.

So our contribution is *not* in the line of research concerned with “tractable approximations” of (1.3) (e.g. under some restrictions on  $f$  and/or the family  $\mathcal{M}_a$ ) and should be viewed as complementary to previously cited contributions whose focus is on on scalability.

So, given  $\varepsilon > 0$  fixed, a family  $\mathcal{M}_a$  (e.g. as in Examples 1.1, 1.2, 1.3, 1.4, 1.5, 1.6) and an arbitrary polynomial  $f$ , our main contribution is to provide rigorous and accurate inner approximations  $(\mathbf{X}_\varepsilon^d)_{d \in \mathbb{N}} \subset \mathbf{X}_\varepsilon^*$  of the set  $\mathbf{X}_\varepsilon^*$ , that converge to  $\mathbf{X}_\varepsilon^*$  in a precise sense as  $d$  increases. More precisely:

(i) We provide a nested sequence of *inner* approximations of the set  $\mathbf{X}_\varepsilon^*$  in (1.3), in the form:

$$(1.6) \quad \mathbf{X}_\varepsilon^d := \{ \mathbf{x} \in \mathbf{X} : w_d(\mathbf{x}) < \varepsilon \}, \quad d \in \mathbb{N},$$

where  $w_d$  is a polynomial of degree at most  $d$ , and  $\mathbf{X}_\varepsilon^d \subset \mathbf{X}_\varepsilon^{d+1} \subset \mathbf{X}_\varepsilon^*$  for every  $d$ .

(ii) We obtain the strong and highly desirable asymptotic guarantee:

$$(1.7) \quad \lim_{d \rightarrow \infty} \lambda(\mathbf{X}_\varepsilon^* \setminus \mathbf{X}_\varepsilon^d) = 0,$$

where  $\lambda$  is the Lebesgue measure on  $\mathbf{X}$ . To the best of our knowledge it is the first result of this kind at this level of generality. Importantly, the “volume” convergence

(1.7) is obtained with *no* assumption of convexity on the set  $\mathbf{X}_\varepsilon^*$  (and indeed in general  $\mathbf{X}_\varepsilon^*$  is not convex).

(iii) Last but not least, the same approach is valid with same conclusions for the more intricate case of *joint* chance-constraints, that is, probabilistic constraints of the form

$$\text{Prob}_\mu(f_j(\mathbf{x}, \omega) > 0, \quad j = 1, \dots, s_f) > 1 - \varepsilon, \quad \forall \mu \in \mathcal{M}_{\mathbf{a}},$$

(for some given polynomials  $(f_j) \subset \mathbb{R}[\mathbf{x}, \omega]$ ). Remarkably, such constraints which are notoriously difficult to handle in general, are relatively easy to incorporate in our formulation.

We emphasize that our approach is a non trivial extension of the numerical scheme proposed in [20] for approximating  $\mathbf{X}_\varepsilon^*$  when  $\mathcal{M}_{\mathbf{a}}$  is a singleton (i.e., for standard chance-constraints).

**Methodology.** The approach that we propose for determining the set  $\mathbf{X}_\varepsilon^d$  defined in (1.6) is very similar in spirit to that in [15] and [17], and a non trivial extension of the more recent work [20] where only a single distribution  $\mu$  is considered. It is an additional illustration of the versatility of the Generalized Moment Problem (GMP) model and the moment-SOS approach outside the field of optimization. Indeed we also define an infinite-dimensional LP problem  $\mathbf{P}$  in an appropriate space of measures and a sequence of semidefinite relaxations  $(\mathbf{P}_d)_{d \in \mathbb{N}}$  of  $\mathbf{P}$ , whose associated monotone sequence of optimal values  $(\rho_d)_{d \in \mathbb{N}}$  converges to the optimal value  $\rho$  of  $\mathbf{P}$ . An optimal solution of this LP is a measure  $\phi^*$  on  $\mathbf{X} \times \Omega$ . In its disintegration  $\hat{\phi}^*(d\omega|\mathbf{x}) d\mathbf{x}$ , the conditional probability  $\hat{\phi}^*(d\omega|\mathbf{x})$  is a measure  $\mu_{\mathbf{a}(\mathbf{x})}$ , for some  $\mathbf{a}(\mathbf{x}) \in \mathbf{A}$ , which identifies the worst-case distribution at  $\mathbf{x} \in \mathbf{X}$ .

At an optimal solution of the dual of the semidefinite relaxation  $(\mathbf{P}_d)$ , we obtain a polynomial  $w_d$  of degree  $2d$  whose sub-level set  $\{\mathbf{x} \in \mathbf{X} : w_d(\mathbf{x}) < 0\}$  is precisely the desired approximation  $\mathbf{X}_\varepsilon^d$  of  $\mathbf{X}_\varepsilon^*$  in (1.3); in fact the sets  $(\mathbf{X}_\varepsilon^d)_{d \in \mathbb{N}}$  provide a sequence of *inner* approximations of  $\mathbf{X}_\varepsilon^*$ .

At last but not least and as in [20], the support  $\Omega$  of  $\mu \in \mathcal{M}_{\mathbf{a}}$  and the set  $\{(\mathbf{x}, \omega) : f(\mathbf{x}, \omega) > 0\}$  are *not* required to be compact, which includes the important case where  $\mu$  can be a mixture of normal or exponential distributions.

As already mentioned, our methodology is *not* a straightforward extension of the work in [20] where  $\mathcal{M}_{\mathbf{a}}$  is a singleton and  $\mu$  can be arbitrary provided that its moments are known. Indeed in the present framework and in contrast to the singleton case treated in [20], we do *not* know a sequence of moments because we do not know the exact distribution  $\mu$  of the noise  $\omega$ . For instance, some measurability issues (e.g. existence of a measurable selector) not present in [20], arise. Also and in contrast to [20], we cannot define outer approximations by passing to the complement of  $\mathbf{X}_\varepsilon^*$ . Therefore some special property of the family  $\mathcal{M}_{\mathbf{a}}$  has to be exploited and indeed, crucial in our approach are the following properties of elements  $\mu_{\mathbf{a}}$ ,  $\mathbf{a} \in \mathbf{A}$ , all satisfied in Examples 1.1, 1.2, 1.3, 1.4, 1.5, and 1.6, and their natural multivariate extensions; see §7.5.

- (i) For every  $\beta \in \mathbb{N}$ :  $\int_{\Omega} \omega^\beta d\mu_{\mathbf{a}}(\omega) = p_\beta(\mathbf{a})$ , for some polynomial<sup>2</sup>  $p_\beta \in \mathbb{R}[\mathbf{a}]$ .
- (ii) For every bounded measurable (resp. continuous) function  $h$  on  $\mathbf{X} \times \Omega$ , the function  $(\mathbf{x}, \mathbf{a}) \mapsto \int_{\Omega} h d\mu_{\mathbf{a}}$  is bounded measurable (resp. continuous),

<sup>2</sup>Could be relaxed to a rational function  $p_\beta(\mathbf{a})/q(\mathbf{a})$  for all  $\beta$  and some polynomial  $q \in \mathbb{R}[\mathbf{a}]$ .

(iii) For some  $c > 0$ ,  $\sup_{\mathbf{a} \in \mathbf{A}} \int_{\Omega} \exp(c |\omega_i|) d\mu_{\mathbf{a}}(\omega) < \infty$ , for all  $i$ .

Interestingly, Property (i) has also been exploited recently in Wang et al. [37] to estimate mixtures of densities (satisfying (i)) from observed moments, as then those moments are mixtures of polynomials in the parameters.

Importantly, we also describe how to accelerate the convergence of our approximation scheme. It consists of adding additional constraints in our relaxation scheme, satisfied at every feasible solution of the infinite-dimensional LP. These additional constraints come from a specific application of Stokes' theorem in the spirit of its earlier application in [20] but more intricate and not a direct extension. Indeed, in the framework of our infinite-dimensional LP, it requires to define a measure with support on  $\mathbf{X} \times \Omega \times \mathbf{A}$  (instead of  $\mathbf{X} \times \Omega$  in [20]) which when passing to relaxations of the LP, results in semidefinite programs of larger size (hence more difficult to solve). However, this price to pay can be profitable because the resulting convergence is expected to be significantly faster.

**Pros and cons.** On a positive side, our approach solves a difficult and challenging mathematical problem as it provides a nested hierarchy of inner approximations  $(\mathbf{X}_{\varepsilon}^d)_{d \in \mathbb{N}}$  of  $\mathbf{X}_{\varepsilon}^*$  which converges to  $\mathbf{X}_{\varepsilon}^*$  as  $d$  increases, a highly desirable feature. Also for every (and especially small)  $d$ , whenever not empty the set  $\mathbf{X}_{\varepsilon}^d$  is a valid (perhaps very conservative if  $d$  is small) inner approximation of  $\mathbf{X}_{\varepsilon}^*$  which can be exploited in applications if needed.

On a negative side, this methodology is computationally expensive, especially to obtain a very good inner approximation  $\mathbf{X}_{\varepsilon}^d$  of  $\mathbf{X}_{\varepsilon}^*$ . Therefore and so far, for accurate approximations this approach is limited to relatively small size problems. But again, recall that this approximation problem is a difficult challenge and at least, our approach with strong asymptotic guarantees provides insights and indications on possible routes to follow if one wishes to scale the method to address larger size problems. For instance, an interesting issue not discussed here is to investigate whether sparsity patterns already exploited in polynomial optimization (e.g. as in Waki et al. [36]) can be exploited in this context.

## 2. NOTATION, DEFINITIONS AND PRELIMINARIES

**2.1. Notation and definitions.** Let  $\mathbb{R}[\mathbf{x}]$  be the ring of polynomials in the variables  $\mathbf{x} = (x_1, \dots, x_n)$  and let  $\mathbb{R}[\mathbf{x}]_d$  be the vector space of polynomials of degree at most  $d$  whose dimension is  $s(d) := \binom{n+d}{n}$ . For every  $d \in \mathbb{N}$ , let  $\mathbb{N}_d^n := \{\alpha \in \mathbb{N}^n : |\alpha| (= \sum_i \alpha_i) \leq d\}$ , and let  $\mathbf{v}_d(\mathbf{x}) = (\mathbf{x}^{\alpha})$ ,  $\alpha \in \mathbb{N}_d^n$ , be the vector of monomials of the canonical basis  $(\mathbf{x}^{\alpha})$  of  $\mathbb{R}[\mathbf{x}]_d$ . A polynomial  $p \in \mathbb{R}[\mathbf{x}]_d$  is written

$$\mathbf{x} \mapsto p(\mathbf{x}) = \sum_{\alpha \in \mathbb{N}_d^n} p_{\alpha} \mathbf{x}^{\alpha},$$

for some vector of coefficients  $\mathbf{p} = (p_{\alpha}) \in \mathbb{R}^{s(d)}$ .

Given a closed set  $\mathcal{X} \subset \mathbb{R}^{\ell}$ , denote by  $\mathcal{B}(\mathcal{X})$  the Borel  $\sigma$ -field of  $\mathcal{X}$ ,  $\mathcal{P}(\mathcal{X})$  the space of probability measures on  $\mathcal{X}$  and by  $\mathcal{B}(\mathcal{X})$  the space of bounded measurable functions on  $\mathcal{X}$ . We also denote by  $\mathcal{M}(\mathcal{X})$  the space of finite signed Borel measures on  $\mathcal{X}$  and by  $\mathcal{M}_+(\mathcal{X})$  its subset of finite (positive) measures on  $\mathcal{X}$ .

**Moment matrix.** Given a sequence  $\mathbf{y} = (y_\alpha)_{\alpha \in \mathbb{N}^n}$ , let  $L_{\mathbf{y}} : \mathbb{R}[\mathbf{x}] \rightarrow \mathbb{R}$  be the linear (Riesz) functional

$$f (= \sum_{\alpha} f_{\alpha} \mathbf{x}^{\alpha}) \mapsto L_{\mathbf{y}}(f) := \sum_{\alpha} f_{\alpha} y_{\alpha}.$$

Given  $\mathbf{y}$  and  $d \in \mathbb{N}$ , the *moment matrix* associated with  $\mathbf{y}$ , is the real symmetric  $s(d) \times s(d)$  matrix  $\mathbf{M}_d(\mathbf{y})$  with rows and columns indexed in  $\mathbb{N}_d^n$  and with entries

$$\mathbf{M}_d(\mathbf{y})(\alpha, \beta) := L_{\mathbf{y}}(\mathbf{x}^{\alpha+\beta}) = y_{\alpha+\beta}, \quad \alpha, \beta \in \mathbb{N}_d^n.$$

A sequence  $\mathbf{y} = (y_{\alpha})_{\alpha \in \mathbb{N}^n}$  has a *representing measure*  $\mu$  if  $y_{\alpha} = \int \mathbf{x}^{\alpha} d\mu$  for all  $\alpha \in \mathbb{N}^n$ ; if  $\mu$  is unique then  $\mu$  said to be *moment determinate*.

A necessary condition for the existence of such a  $\mu$  is that  $\mathbf{M}_d(\mathbf{y}) \succeq 0$  for all  $d$ . But it is only a necessary condition (except in the univariate case  $n = 1$ ). However the following sufficient condition in [24, Proposition 2.37] is very useful:

**Lemma 2.1.** ([24]) *If  $\mathbf{y} = (y_{\alpha})_{\alpha \in \mathbb{N}^n}$  satisfies  $\mathbf{M}_d(\mathbf{y}) \succeq 0$  for all  $d = 0, 1, \dots$  and*

$$(2.1) \quad \sum_{k=1}^{\infty} L_{\mathbf{y}}(x_i^{2k})^{-1/2k} = +\infty, \quad i = 1, \dots, n,$$

*then  $\mathbf{y}$  has a representing measure, and in addition  $\mu$  is moment determinate.*

Condition (2.1) due to Nussbaum is the multivariate generalization of its earlier univariate version due to Carleman; see e.g. [23].

**Localizing matrix.** Given a sequence  $\mathbf{y} = (y_{\alpha})_{\alpha \in \mathbb{N}^n}$ , and a polynomial  $g \in \mathbb{R}[\mathbf{x}]$ , the *localizing moment matrix* associated with  $\mathbf{y}$  and  $g$ , is the real symmetric  $s(d) \times s(d)$  matrix  $\mathbf{M}_d(g\mathbf{y})$  with rows and columns indexed in  $\mathbb{N}_d^n$  and with entries

$$\begin{aligned} \mathbf{M}_d(g\mathbf{y})(\alpha, \beta) &:= L_{\mathbf{y}}(g(\mathbf{x}) \mathbf{x}^{\alpha+\beta}) \\ &= \sum_{\gamma} g_{\gamma} y_{\alpha+\beta+\gamma}, \quad \alpha, \beta \in \mathbb{N}_d^n. \end{aligned}$$

**Disintegration.** Given a probability measure  $\mu$  on a cartesian product  $\mathcal{X} \times \mathcal{Y}$  of topological spaces, we may decompose  $\mu$  into its marginal  $\mu_{\mathbf{x}}$  on  $\mathcal{X}$  and a stochastic kernel (or conditional probability measure  $\hat{\mu}(d\mathbf{y}|\cdot)$ ) on  $\mathcal{Y}$  given  $\mathcal{X}$ , that is:

- For every  $\mathbf{x} \in \mathcal{X}$ ,  $\hat{\mu}(d\mathbf{y}|\mathbf{x}) \in \mathcal{P}(\mathcal{Y})$ , and
- For every  $B \in \mathcal{B}(\mathcal{Y})$ , the function  $\mathbf{x} \mapsto \hat{\mu}(B|\mathbf{x})$  is measurable.

Then

$$\mu(A \times B) = \int_A \hat{\mu}(B|\mathbf{x}) \mu_{\mathbf{x}}(d\mathbf{x}), \quad \forall A \in \mathcal{B}(\mathcal{X}), B \in \mathcal{B}(\mathcal{Y}).$$

**2.2. The family  $\mathcal{M}_{\mathbf{a}}$ .** Let  $\Omega \subset \mathbb{R}^p$  be the “noise” (or disturbance) space. Let  $\mathbf{A} \subset \mathbb{R}^t$  be a compact set and for every  $\mathbf{a} \in \mathbf{A}$ , let  $\mu_{\mathbf{a}} \in \mathcal{P}(\Omega)$ .

**Assumption 2.2.** *The set  $\{\mu_{\mathbf{a}} : \mathbf{a} \in \mathbf{A}\} \subset \mathcal{P}(\Omega)$  satisfies the following:*

- (i) *For every  $B \in \mathcal{B}(\Omega)$ , the function  $\mathbf{a} \mapsto \mu_{\mathbf{a}}(B)$  is measurable.*
- (ii) *For every  $\beta \in \mathbb{N}$ :*

$$(2.2) \quad \int_{\Omega} \omega^{\beta} d\mu_{\mathbf{a}}(\omega) = p_{\beta}(\mathbf{a}), \quad \forall \mathbf{a} \in \mathbf{A},$$

*for some polynomial  $p_{\beta} \in \mathbb{R}[\mathbf{a}]$ .*

- (iii) *For every  $\mathbf{a} \in \mathbf{A}$  and every polynomial  $g \in \mathbb{R}[\omega]$ ,  $\mu_{\mathbf{a}}(\{\omega : g(\omega) = 0\}) = 0$ .*



(iv) For every bounded measurable (resp. bounded continuous) function  $q$  on  $\mathbf{X} \times \Omega$ , the function

$$(\mathbf{x}, \mathbf{a}) \mapsto Q(\mathbf{x}, \mathbf{a}) := \int_{\Omega} q(\mathbf{x}, \omega) d\mu_{\mathbf{a}}(\omega),$$

is bounded measurable (resp. bounded continuous) on  $\mathbf{X} \times \mathbf{A}$ .

For instance if  $d\mu_{\mathbf{a}}(\omega) = \theta(\mathbf{a}, \omega) d\omega$  for some measurable density  $\theta(\mathbf{a}, \cdot)$  on  $\Omega$ , then Assumption 2.2(i) follows from Fubini-Tonelli's Theorem [10], Assumption 2.2(iii) is also satisfied. As already mentioned Assumption 2.2(ii) is also satisfied in Example 1.1, 1.2, and 1.6, as well as in their multivariate extensions. Assumption 2.2(iv) is also satisfied in Example 1.1, 1.2 and 1.6, and their natural multivariate extensions. For instance, in Example 1.1 where  $\mathcal{M}_{\mathbf{a}}$  is the set of all possible mixtures of univariate Gaussian probability distributions with mean and standard deviation  $(a, \sigma) \in \mathbf{A}$ , the function

$$Q(\mathbf{x}, \mathbf{a}) := \int_{\Omega} q(\mathbf{x}, \omega) d\mu_{\mathbf{a}} = \frac{1}{\sqrt{2\pi}} \int_{\Omega} q(\mathbf{x}, (\sigma\omega + a)) \exp(-\omega^2/2) d\omega,$$

is bounded measurable (resp. continuous) in  $\mathbf{a} \in \mathbf{A}$  whenever  $q$  is bounded measurable (resp. continuous) on  $\mathbf{X} \times \Omega$ .

In addition, if  $\Omega$  is non compact then we also need:

**Assumption 2.3.** (If  $\Omega \subset \mathbb{R}^p$  is unbounded):

There exists  $c, \gamma > 0$  such that for every  $i = 1, \dots, p$ :

$$(2.3) \quad \sup_{\mathbf{a} \in \mathbf{A}} \int_{\Omega} \exp(c|\omega_i|) d\mu_{\mathbf{a}}(\omega) < \gamma.$$

This assumption is also satisfied in Example 1.1, 1.2 and 1.6, and their natural multivariate extensions.

**Definition 2.4.**  $\mathcal{M}_{\mathbf{a}} \subset \mathcal{P}(\Omega)$  is the space of all possible mixtures of probability measures  $\mu_{\mathbf{a}}$ ,  $\mathbf{a} \in \mathbf{A}$ . That is,  $\mu \in \mathcal{M}_{\mathbf{a}}$  if and only if there exists  $\varphi \in \mathcal{P}(\mathbf{A})$  such that

$$(2.4) \quad \mu(B) = \int_{\mathbf{A}} \mu_{\mathbf{a}}(B) d\varphi(\mathbf{a}), \quad \forall B \in \mathcal{B}(\mathbf{A}).$$

(By Assumption 2.2(i),  $\mu$  is well-defined.) In particular  $\mu_{\mathbf{a}} \in \mathcal{M}_{\mathbf{a}}$  for all  $\mathbf{a} \in \mathbf{A}$ .

Let  $\mathbf{X} \subset \mathbb{R}^n$  and  $\mathbf{A} \subset \mathbb{R}^t$  be a compact basic semi-algebraic sets and let  $\lambda$  be the Lebesgue measure on  $\mathbf{X}$ , scaled to be a probability measure on  $\mathbf{X}$ . We assume that  $\mathbf{X}$  is simple enough so that all moments of  $\lambda$  are easily calculated or available in closed-form. Typically  $\mathbf{X}$  is a box, a simplex, an ellipsoid, etc. The set  $\Omega \subset \mathbb{R}^p$  is also a basic semi-algebraic set not necessarily compact (for instance it can be  $\mathbb{R}^p$  or the positive orthant  $\mathbb{R}_+^p$ ).

**Definition 2.5.** Given a measure  $\psi$  on  $\mathbf{X} \times \mathbf{A}$  define  $\psi'$  on  $\mathbf{X} \times \mathbf{A} \times \Omega$  by:

$$\psi'(B, C, D) = \int_{B \times C} \mu_{\mathbf{a}}(D) d\psi(\mathbf{x}, \mathbf{a}), \quad B \in \mathcal{B}(\mathbf{X}), C \in \mathcal{B}(\mathbf{A}), D \in \mathcal{B}(\Omega),$$

which is well defined by Assumption 2.2(i). Its marginal  $\psi'_{\mathbf{x}, \mathbf{a}}$  on  $\mathbf{X} \times \mathbf{A}$  is  $\psi$  and  $\hat{\psi}'(\cdot | \mathbf{x}, \mathbf{a}) = \mu_{\mathbf{a}}$

Recall that  $\mathcal{B}(\mathbf{X} \times \Omega)$  is the space of bounded measurable functions on  $\mathbf{X} \times \Omega$ . Define the linear mapping  $\mathbf{T} : \mathcal{B}(\mathbf{X} \times \Omega) \rightarrow \mathcal{B}(\mathbf{X} \times \mathbf{A})$  by:

$$(2.5) \quad g \mapsto \mathbf{T}g(\mathbf{x}, \mathbf{a}) := \int_{\Omega} g(\mathbf{x}, \omega) d\mu_{\mathbf{a}}(\omega), \quad \mathbf{a} \in \mathbf{A},$$

which is well-defined by Assumption 2.2(iv). Therefore one may define the *adjoint* linear mapping  $\mathbf{T}^* : \mathcal{M}(\mathbf{X} \times \mathbf{A}) \rightarrow \mathcal{M}(\mathbf{X} \times \Omega)$  by:

$$\begin{aligned} \langle g, \mathbf{T}^*\psi \rangle & \quad \left( = \int_{\mathbf{X} \times \Omega} g(\mathbf{x}, \omega) d\mathbf{T}^*\psi(\mathbf{x}, \omega) \right) = \langle \mathbf{T}g, \psi \rangle \\ & \quad \left( = \int_{\mathbf{X} \times \mathbf{A}} \left( \int_{\Omega} g(\mathbf{x}, \omega) d\mu_{\mathbf{a}}(\omega) \right) d\psi(\mathbf{x}, \mathbf{a}) \right), \end{aligned}$$

for all  $g \in \mathcal{B}(\mathbf{X} \times \Omega)$  and all  $\psi \in \mathcal{M}(\mathbf{X} \times \mathbf{A})$ .

**Lemma 2.6.** *Let  $\mathbf{T}$  be as (2.5). Then for every  $\psi \in \mathcal{M}_+(\mathbf{X} \times \mathbf{A})$ ,  $\mathbf{T}^*\psi = \psi'_{\mathbf{x}, \omega}$  where  $\psi'_{\mathbf{x}, \omega}$  is the marginal on  $\mathbf{X} \times \Omega$  of the measure  $\psi' \in \mathcal{M}_+(\mathbf{X} \times \mathbf{A} \times \Omega)$  in Definition 2.5.*

*Proof.* Let  $g \in \mathcal{B}(\mathbf{X} \times \Omega)$  fixed, arbitrary. Then:

$$\begin{aligned} \langle g, \mathbf{T}^*\psi \rangle = \langle \mathbf{T}g, \psi \rangle & = \int_{\mathbf{X} \times \mathbf{A}} \left( \int_{\Omega} g(\mathbf{x}, \omega) \mu_{\mathbf{a}}(d\omega) \right) d\psi(\mathbf{x}, \mathbf{a}) \\ & = \int_{\mathbf{X} \times \mathbf{A}} \left( \int_{\Omega} g(\mathbf{x}, \omega) \hat{\psi}'(d\omega | \mathbf{x}, \mathbf{a}) \right) d\psi(\mathbf{x}, \mathbf{a}) \\ & = \int_{\mathbf{X} \times \mathbf{A} \times \Omega} g(\mathbf{x}, \omega) d\psi'(\mathbf{x}, \mathbf{a}, \omega) \\ & = \int_{\mathbf{X} \times \Omega} g(\mathbf{x}, \omega) d\psi'_{\mathbf{x}, \omega}(\mathbf{x}, \omega) = \langle g, \psi'_{\mathbf{x}, \omega} \rangle. \end{aligned}$$

As this holds for every  $g \in \mathcal{B}(\mathbf{X} \times \Omega)$ , it follows that  $\mathbf{T}^*\psi = \psi'_{\mathbf{x}, \omega}$ .  $\square$

**Lemma 2.7.** *Let Assumption 2.2 hold. Then the mapping  $\mathbf{T}$  in (2.5) extends to polynomials. Moreover,  $\mathbf{T}(\mathbb{R}[\mathbf{x}, \omega]) \subset \mathbb{R}[\mathbf{x}, \mathbf{a}]$  and*

$$(2.6) \quad \langle h, \mathbf{T}^*\psi \rangle = \langle \mathbf{T}h, \psi \rangle, \quad \forall h \in \mathbb{R}[\mathbf{x}, \omega], \forall \psi \in \mathcal{M}_+(\mathbf{X} \times \mathbf{A}).$$

*Proof.* Let  $h \in \mathbb{R}[\mathbf{x}, \omega]$  be fixed, arbitrary and write  $h(\mathbf{x}, \omega) = \sum_{\alpha, \beta} h_{\alpha\beta} \mathbf{x}^{\alpha} \omega^{\beta}$ . Then by Assumption 2.2(ii):

$$\mathbf{T}h(\mathbf{x}, \mathbf{a}) := \sum_{\alpha, \beta} h_{\alpha\beta} \mathbf{x}^{\alpha} \int_{\Omega} \omega^{\beta} d\mu_{\mathbf{a}} = \sum_{\alpha, \beta} h_{\alpha\beta} \mathbf{x}^{\alpha} p_{\beta}(\mathbf{a}) \in \mathbb{R}[\mathbf{x}, \mathbf{a}].$$

Hence  $\langle \mathbf{T}h, \psi \rangle = \int_{\mathbf{X} \times \mathbf{A}} \sum_{\alpha, \beta} h_{\alpha\beta} \mathbf{x}^\alpha p_\beta(\mathbf{a}) d\psi(\mathbf{x}, \mathbf{a})$ . Next, recalling the definition of  $\psi'$  and  $\psi'_{\mathbf{x}, \omega}$ :

$$\begin{aligned} \int_{\mathbf{X} \times \mathbf{A}} \sum_{\alpha, \beta} h_{\alpha\beta} \mathbf{x}^\alpha p_\beta(\mathbf{a}) d\psi(\mathbf{x}, \mathbf{a}) &= \int_{\mathbf{X} \times \mathbf{A}} \left( \int_{\Omega} h(\mathbf{x}, \omega) \mu_{\mathbf{a}}(d\omega) \right) d\psi(\mathbf{x}, \mathbf{a}) \\ &= \int_{\mathbf{X} \times \Omega \times \mathbf{A}} h(\mathbf{x}, \omega) d\psi'(\mathbf{x}, \omega, \mathbf{a}) \\ &= \int_{\mathbf{X} \times \Omega} h(\mathbf{x}, \omega) d\psi'_{\mathbf{x}, \omega}(\mathbf{x}, \omega) \\ &= \int_{\mathbf{X} \times \Omega} h(\mathbf{x}, \omega) d\mathbf{T}^* \psi = \langle h, \mathbf{T}^* \psi \rangle, \end{aligned}$$

which yields (2.6).  $\square$

### 3. AN IDEAL INFINITE-DIMENSIONAL LP PROBLEM

Let  $f \in \mathbb{R}[\mathbf{x}, \omega]$  be a given polynomial and with  $\varepsilon > 0$  fixed, consider the set  $\mathbf{X}_\varepsilon^*$  defined in (1.2). Let

$$(3.1) \quad \mathbf{K} := \{(\mathbf{x}, \omega) \in \mathbf{X} \times \Omega : f(\mathbf{x}, \omega) \leq 0\}$$

$$(3.2) \quad \mathbf{K}_{\mathbf{x}} := \{\omega \in \Omega : (\mathbf{x}, \omega) \in \mathbf{K}\}, \quad \mathbf{x} \in \mathbf{X}.$$

$$(3.3) \quad \Omega := \{\omega \in \mathbb{R}^p : s_\ell(\omega) \geq 0, \dots, \bar{s}\},$$

for some polynomials  $(s_\ell) \subset \mathbb{R}[\omega]$ . In particular if  $s = 0$  then  $\Omega = \mathbb{R}^p$ .

**Lemma 3.1.** *For each  $\mathbf{x} \in \mathbf{X}$  there exists measurable mappings  $\mathbf{x} \mapsto \mathbf{a}(\mathbf{x}) \in \mathbf{A}$  and  $\mathbf{x} \mapsto \kappa(\mathbf{x}) \in \mathbf{A}$  such that:*

$$(3.4) \quad \kappa(\mathbf{x}) = \max\{\mu(\mathbf{K}_{\mathbf{x}}) : \mu \in \mathcal{M}_{\mathbf{a}}\} = \max\{\mu_{\mathbf{a}}(\mathbf{K}_{\mathbf{x}}) : \mathbf{a} \in \mathbf{A}\} = \mu_{\mathbf{a}(\mathbf{x})}(\mathbf{K}_{\mathbf{x}}).$$

*Proof.* With  $\mathbf{x} \in \mathbf{X}$  fixed, let  $\theta := \sup_{\mu} \{\mu(\mathbf{K}_{\mathbf{x}}) : \mu \in \mathcal{M}_{\mathbf{a}}\}$ . For every  $\mu \in \mathcal{M}_{\mathbf{a}}$ , there exists  $\varphi \in \mathcal{P}(\mathbf{A})$  such that  $\mu(\mathbf{K}_{\mathbf{x}}) = \int_{\mathbf{A}} \mu_{\mathbf{a}}(\mathbf{K}_{\mathbf{x}}) d\varphi(\mathbf{a})$  and so  $\mu(\mathbf{K}_{\mathbf{x}}) \leq \theta$  for all  $\mu \in \mathcal{M}_{\mathbf{a}}$ . Next let  $v : \mathbf{X} \times \mathbf{A} \rightarrow [0, 1]$  be given by  $v(\mathbf{x}, \mathbf{a}) := \mu_{\mathbf{a}}(\mathbf{K}_{\mathbf{x}})$ . By construction  $0 \leq v \leq 1$  on  $\mathbf{X} \times \mathbf{A}$  and if  $v(\mathbf{x}, \cdot)$  is upper-semicontinuous on  $\mathbf{A}$  for every  $\mathbf{x} \in \mathbf{X}$ , then by [22, Proposition 4.4, p. 2018] there exists a *measurable selector*  $\mathbf{x} \mapsto \mathbf{a}(\mathbf{x}) \in \mathbf{A}$ ,  $\mathbf{x} \in \mathbf{X}$ , such that  $v(\mathbf{x}, \mathbf{a}(\mathbf{x})) = \max\{v(\mathbf{x}, \mathbf{a}) : \mathbf{a} \in \mathbf{A}\}$ , that is, the desired result (3.4) holds.

So it remains to prove that  $v(\mathbf{x}, \cdot)$  is upper-semicontinuous on  $\mathbf{A}$  for every  $\mathbf{x} \in \mathbf{X}$ . In fact we even prove that  $v(\mathbf{x}, \cdot)$  is continuous on  $\mathbf{A}$  for every  $\mathbf{x} \in \mathbf{X}$ . So let  $(a_n)_{n \in \mathbb{N}} \subset \mathbf{A}$  with  $a_n \rightarrow \mathbf{a} \in \mathbf{A}$  as  $n \rightarrow \infty$ . Let  $q$  be an arbitrary bounded continuous function on  $\Omega$ . Then by Assumption 2.2(iv),

$$\lim_{n \rightarrow \infty} \int_{\Omega} q d\mu_{a_n}(\omega) = \lim_{n \rightarrow \infty} Q(a_n) = Q(\mathbf{a}) = \int_{\Omega} q d\mu_{\mathbf{a}}(\omega),$$

which proves that  $\mu_{a_n} \Rightarrow \mu_{\mathbf{a}}$  as  $n \rightarrow \infty$  (where  $\Rightarrow$  denotes the weak convergence of probability measures; see Billingsley [4]). In addition, in view of the definition of  $\mathbf{K}_{\mathbf{x}}$  in (3.2), its boundary  $\partial \mathbf{K}_{\mathbf{x}}$  is contained in the zero set of some polynomials and therefore, by Assumption 2.2(iii),  $\mu_{a_n}(\partial \mathbf{K}_{\mathbf{x}}) = \mu_{\mathbf{x}}(\partial \mathbf{K}_{\mathbf{x}}) = 0$  for all  $n$  (i.e.  $\partial \mathbf{K}_{\mathbf{x}}$  is

a  $\mu_{\mathbf{a}_n}$ -continuity set). Hence by the Portmanteau theorem [4, Theorem 2.1, p. 11] it follows that

$$\lim_{n \rightarrow \infty} \mu_{\mathbf{a}_n}(\mathbf{K}_{\mathbf{x}}) = \lim_{n \rightarrow \infty} v(\mathbf{x}, \mathbf{a}_n) = \mu_{\mathbf{a}}(\mathbf{K}_{\mathbf{x}}) = v(\mathbf{x}, \mathbf{a}),$$

i.e.,  $v(\mathbf{x}, \cdot)$  is continuous on  $\mathbf{A}$  for every  $\mathbf{x} \in \mathbf{X}$ . In addition  $\kappa(\mathbf{x}) = v(\mathbf{x}, \mathbf{a}(\mathbf{x}))$  is also measurable.  $\square$

Observe that for all  $\mathbf{x} \in \mathbf{X}$ ,  $\kappa(\mathbf{x}) = \mu_{\mathbf{a}(\mathbf{x})}(\mathbf{K}_{\mathbf{x}}) = 0$  whenever  $\mathbf{K}_{\mathbf{x}} = \emptyset$ . Next, recall that for every  $\mathbf{x} \in \mathbf{X}$ :

$$\kappa(\mathbf{x}) = \max_{\mu} \{ \mu(\mathbf{K}_{\mathbf{x}}) : \mu \in \mathcal{M}_{\mathbf{a}} \} = \max_{\mu} \{ \text{Prob}_{\mu}(f(\mathbf{x}, \omega) \leq 0) : \mu \in \mathcal{M}_{\mathbf{a}} \}.$$

and so with  $\mathbf{K}_{\mathbf{x}}^c := \Omega \setminus \mathbf{K}_{\mathbf{x}}$ ,

$$\mu_{\mathbf{a}(\mathbf{x})}(\mathbf{K}_{\mathbf{x}}^c) = \min_{\mu} \{ \mu(\mathbf{K}_{\mathbf{x}}^c) : \mu \in \mathcal{M}_{\mathbf{a}} \} = \min_{\mu} \{ \text{Prob}_{\mu}(f(\mathbf{x}, \omega) > 0) : \mu \in \mathcal{M}_{\mathbf{a}} \}.$$

So the set  $\mathbf{X}_{\varepsilon}^*$  in (1.3) also reads:

$$\mathbf{X}_{\varepsilon}^* = \{ \mathbf{x} \in \mathbf{X} : \mu_{\mathbf{a}(\mathbf{x})}(\mathbf{K}_{\mathbf{x}}^c) > 1 - \varepsilon \} = \{ \mathbf{x} \in \mathbf{X} : \kappa(\mathbf{x}) < \varepsilon \}.$$

Let  $\lambda$  be the Lebesgue measure on  $\mathbf{X}$ , normalized to a probability measure, and consider the infinite-dimensional linear program (LP):

$$(3.5) \quad \begin{aligned} \rho = \sup_{\phi, \psi \geq 0} \quad & \{ \phi(\mathbf{K}) : \phi \leq \mathbf{T}^* \psi; \quad \psi_{\mathbf{x}} = \lambda, \\ & \phi \in \mathcal{M}_+(\mathbf{K}), \psi \in \mathcal{P}(\mathbf{X} \times \mathbf{A}) \}, \end{aligned}$$

where  $\mathbf{T}^*$  is defined in Lemma 2.6.

**Theorem 3.2.** *The infinite dimensional LP (3.5) has optimal value  $\rho = \int_{\mathbf{X}} \kappa(\mathbf{x}) d\mathbf{x}$ . Moreover, the feasible pair  $(\phi^*, \psi^*)$  with*

$$d\phi^*(\mathbf{x}, \omega) := \mathbf{1}_{\mathbf{K}}(\mathbf{x}, \omega) \mu_{\mathbf{a}(\mathbf{x})}(d\omega) d\lambda(\mathbf{x}), \quad d\psi^*(\mathbf{x}, \mathbf{a}) = \delta_{\mathbf{a}(\mathbf{x})}(d\mathbf{a}) \lambda(d\mathbf{x}),$$

is an optimal solution of (3.5), with  $\mathbf{x} \mapsto (\mathbf{a}(\mathbf{x}), \kappa(\mathbf{x}))$  as in Lemma 3.1.

*Proof.* Let  $(\phi, \psi)$  be an arbitrary feasible solution. Then

$$\begin{aligned} \phi(\mathbf{K}) = \langle \mathbf{1}, \phi \rangle & \leq \langle \mathbf{1}_{\mathbf{K}}, \mathbf{T}^* \psi \rangle \\ & = \langle \mathbf{T} \mathbf{1}_{\mathbf{K}}, \psi \rangle = \int_{\mathbf{X} \times \mathbf{A}} \mu_{\mathbf{a}}(\mathbf{K}_{\mathbf{x}}) d\psi(\mathbf{x}, \mathbf{a}) \\ & = \int_{\mathbf{X}} \left( \int_{\mathbf{A}} \mu_{\mathbf{a}}(\mathbf{K}_{\mathbf{x}}) \hat{\psi}(d\mathbf{a}|\mathbf{x}) \right) \lambda(d\mathbf{x}) \\ & \leq \int_{\mathbf{X}} \mu_{\mathbf{a}(\mathbf{x})}(\mathbf{K}_{\mathbf{x}}) \lambda(d\mathbf{x}) \quad [\text{by Lemma 3.1}] \\ & = \int_{\mathbf{X}} \kappa(\mathbf{x}) \lambda(d\mathbf{x}). \end{aligned}$$

Next let  $d\phi^*(\mathbf{x}, \omega) = \mathbf{1}_{\mathbf{K}}(\mathbf{x}, \omega) \mu_{\mathbf{a}(\mathbf{x})}(d\omega) \lambda(d\mathbf{x})$  and  $d\psi^*(\mathbf{x}, \mathbf{a}) = \delta_{\mathbf{a}(\mathbf{x})}(d\mathbf{a}) \lambda(d\mathbf{x})$  with  $\mathbf{x} \mapsto \mathbf{a}(\mathbf{x})$  as in Lemma 3.1. Then  $\phi^* \in \mathcal{M}_+(\mathbf{K})$  and  $\phi^* \leq \mathbf{T}^* \psi^*$ . Moreover:

$$\phi^*(\mathbf{K}) = \int_{\mathbf{X}} \left( \int_{\mathbf{K}_{\mathbf{x}}} d\mu_{\mathbf{a}(\mathbf{x})}(\omega) \right) \lambda(d\mathbf{x}) = \int_{\mathbf{X}} \kappa(\mathbf{x}) \lambda(d\mathbf{x})$$

as  $\mu_{\mathbf{a}(\mathbf{x})}(\mathbf{K}_{\mathbf{x}}) = 0$  whenever  $\mathbf{K}_{\mathbf{x}} = \emptyset$ .  $\square$

Hence, Theorem 3.2 states that in an optimal solution  $(\phi^*, \psi^*)$  of the LP (3.5), at every  $\mathbf{x} \in \mathbf{S}$ , the conditional probability  $\hat{\phi}^*(\cdot|\mathbf{x}) := \mu_{\mathbf{a}(\mathbf{x})} \in \mathcal{M}_{\mathbf{a}}$  identifies the *worst case* noise distribution  $\mu_{\mathbf{a}(\mathbf{x})}$  in  $\mathcal{M}_{\mathbf{a}}$ , that is, the one which maximizes  $\text{Prob}_{\mu}(f(\mathbf{x}, \omega) \leq 0)$  over  $\mathcal{M}_{\mathbf{a}}$ , hence which minimizes  $\text{Prob}_{\mu}(f(\mathbf{x}, \omega) > 0)$  over  $\mathcal{M}_{\mathbf{a}}$ .

**3.1. A dual of (3.5).** Recall that by Lemma 2.7, the mapping  $\mathbf{T}$  extends to polynomials, and so consider the infinite dimensional LP:

$$(3.6) \quad \rho^* = \inf_{h,w} \left\{ \int_{\mathbf{X}} w d\lambda : \begin{array}{l} h(\mathbf{x}, \omega) \geq 1 \quad \text{on } \mathbf{K}, \\ w(\mathbf{x}) - \mathbf{T}h(\mathbf{x}, \mathbf{a}) \geq 0 \quad \text{on } \mathbf{X} \times \mathbf{A}, \\ h \geq 0 \quad \text{on } \mathbf{X} \times \Omega, \\ w \in \mathbb{R}[\mathbf{x}]; h \in \mathbb{R}[\mathbf{x}, \omega]. \end{array} \right.$$

**Theorem 3.3.** *The infinite dimensional LP (3.6) is a dual of (3.5) that is,  $\rho^* \geq \rho$ . In addition, for every feasible solution  $(w, h)$  of (3.6):*

$$(3.7) \quad w(\mathbf{x}) \geq \kappa(\mathbf{x}), \quad \forall \mathbf{x} \in \mathbf{X},$$

with  $\mathbf{x} \mapsto \kappa(\mathbf{x})$  as in Lemma 3.1, and so for every  $\varepsilon > 0$ :

$$(3.8) \quad \mathbf{X}_w := \{\mathbf{x} : w(\mathbf{x}) < \varepsilon\} \subset \{\mathbf{x} : \mu_{\mathbf{a}(\mathbf{x})}(\mathbf{K}_{\mathbf{x}}^c) > 1 - \varepsilon\} = \mathbf{X}_{\varepsilon}^*.$$

Moreover, suppose that there is no duality gap, i.e.,  $\rho^* = \rho$ , and let  $(w_n, h_n)$  be a minimizing sequence of (3.6). Then with  $\|\cdot\|_1$  the norm of  $L_1(\mathbf{X}, \lambda)$ :

$$(3.9) \quad \lim_{n \rightarrow \infty} \|w_n - \kappa\|_1 = 0, \quad \text{and} \quad \lim_{n \rightarrow \infty} \lambda(\mathbf{X}_{\varepsilon}^* \setminus \mathbf{X}_{w_n}) = 0.$$

The proof is postponed to §7.1. Theorem 3.3 is still abstract and the challenge is to define a practical method to compute  $\rho$  and to *construct* effectively, inner approximations of  $\mathbf{X}_{\varepsilon}^*$  which converge to  $\mathbf{X}_{\varepsilon}^*$ , as the approximations  $\mathbf{X}_{w_n}$  in (3.9).

#### 4. A HIERARCHY OF SEMIDEFINITE RELAXATIONS

In this section we provide a numerical scheme to approximate from above the optimal value  $\rho$  of the infinite-dimensional LP (3.5) and its dual (3.6). In addition, from an optimal solution of the approximation of the dual (3.6), one is able to construct *effectively* inner approximations of  $\mathbf{X}_{\varepsilon}^*$  which converge to  $\mathbf{X}_{\varepsilon}^*$ , as the approximations  $H_n$  in (3.9).

As a preliminary, we first show that the measure  $\mathbf{T}\psi^*$  in the constraint  $\phi \leq \mathbf{T}^*\psi$ , identified as  $\psi'_{\mathbf{x}, \omega}$  in Lemma 2.6, can be “handled” through its moments.

**Lemma 4.1.** *Let  $\nu \in \mathcal{P}(\mathbf{X} \times \Omega)$  and  $\psi \in \mathcal{P}(\mathbf{X} \times \mathbf{A})$  with  $\psi_{\mathbf{x}} = \lambda$ , and let*

$$(4.1) \quad \int_{\mathbf{X} \times \Omega} \mathbf{x}^{\alpha} \omega^{\beta} d\nu(\mathbf{x}, \omega) = \int_{\mathbf{X} \times \mathbf{A}} \mathbf{x}^{\alpha} p_{\beta}(\mathbf{a}) d\psi(\mathbf{x}, \mathbf{a}), \quad \forall \alpha \in \mathbb{N}^n, \beta \in \mathbb{N}^p.$$

Then  $\nu = \mathbf{T}^*\psi$ .

The proof is postponed to §7.2.

**4.1. A hierarchy of semidefinite relaxations of (3.5).** The compact basic semi-algebraic sets  $\mathbf{X}$  and  $\mathbf{A}$  are defined by:

$$(4.2) \quad \mathbf{X} := \{\mathbf{x} : g_j(\mathbf{x}) \geq 0, j = 1, \dots, m\}$$

$$(4.3) \quad \mathbf{A} := \{\mathbf{a} \in \mathbb{R}^t : q_\ell(\mathbf{a}) \geq 0, \ell = 1, \dots, L\}$$

for some polynomials  $(g_j) \subset \mathbb{R}[\mathbf{x}]$  and  $(q_\ell) \subset \mathbb{R}[\mathbf{a}]$ . Let  $d_j := \lceil \deg(g_j)/2 \rceil$ ,  $d'_\ell := \lceil \deg(q_\ell)/2 \rceil$ ,  $j = 1, \dots, m$ ,  $\ell = 1, \dots, L$ . Also let  $d_\ell^1 = \lceil \deg(s_\ell)/2 \rceil$ ,  $\ell = 1, \dots, \bar{s}$ . For notational convenience we also define  $g_{m+1}(\mathbf{x}, \omega) = -f(\mathbf{x}, \omega)$  with  $d_{m+1} := \lceil \deg(f)/2 \rceil$ . As  $\mathbf{X}$  and  $\mathbf{A}$  are compact, then  $\mathbf{X} \subset \{\mathbf{x} : \|\mathbf{x}\|^2 \leq M\}$  and  $\mathbf{A} \subset \{\mathbf{a} : \|\mathbf{a}\|^2 \leq M\}$  for some  $M$  sufficiently large. Therefore with no loss of generality we may and will assume that

$$(4.4) \quad g_1(\mathbf{x}) = M - \|\mathbf{x}\|^2, \quad q_1(\mathbf{a}) = M - \|\mathbf{a}\|^2,$$

for some  $M$  sufficiently large. Similarly if  $\Omega$  in (3.3) is compact then we may and will also assume that  $s_1(\omega) = M - \|\omega\|^2$ . This will be very useful as it ensures compactness of the feasible sets of the semidefinite relaxations defined below.

Next, recall that by Assumption 2.2(ii), for every  $\beta \in \mathbb{N}^p$ ,  $\int_{\Omega} \omega^\beta d\mu_{\mathbf{a}}(\omega) = p_\beta(\mathbf{a})$ , for all  $\mathbf{a} \in \mathbf{A}$ , for some polynomial  $p_\beta \in \mathbb{R}[\mathbf{a}]$ .

Consider the following hierarchy of semidefinite programs indexed by  $d \geq d_0 \in \mathbb{N}$ :

$$(4.5) \quad \begin{aligned} \rho_d = & \sup_{\mathbf{y}, \mathbf{u}, \mathbf{v}} y_{00} \\ \text{s.t. } & L_{\mathbf{y}+\mathbf{u}}(\mathbf{x}^\alpha \omega^\beta) - L_{\mathbf{v}}(\mathbf{x}^\alpha p_\beta(\mathbf{a})) = 0, |\alpha + \deg(p_\beta)| \leq 2d, \\ & L_{\mathbf{v}}(\mathbf{x}^\alpha) = \lambda_\alpha, \quad \alpha \in \mathbb{N}_{2d}^n, \\ & \mathbf{M}_d(\mathbf{y}), \mathbf{M}_d(\mathbf{u}), \mathbf{M}_d(\mathbf{v}) \succeq 0, \\ & \mathbf{M}_{d-d_{m+1}}(g_{m+1} \mathbf{y}) \succeq 0, \\ & \mathbf{M}_{d-d_j}(g_j \mathbf{y}), \mathbf{M}_{d-d_j}(g_j \mathbf{u}), \mathbf{M}_d(g_j \mathbf{v}) \succeq 0, \quad j = 1, \dots, m, \\ & \mathbf{M}_{d-d_\ell^1}(s_\ell \mathbf{y}), \mathbf{M}_{d-d_\ell^1}(s_\ell \mathbf{u}) \succeq 0, \quad \ell = 1, \dots, \bar{s}, \\ & \mathbf{M}_{d-d'_\ell}(q_\ell \mathbf{v}) \succeq 0, \quad \ell = 1, \dots, L, \end{aligned}$$

where  $\mathbf{y} = (y_{\alpha\beta})$ ,  $\mathbf{u} = (u_{\alpha\beta})$ ,  $(\alpha, \beta) \in \mathbb{N}^n \times \mathbb{N}^p$  and  $\mathbf{v} = (v_{\alpha\eta})$ ,  $(\alpha, \eta) \in \mathbb{N}^n \times \mathbb{N}^t$ .

**Interpretation of (4.5).** Ideally  $\mathbf{y}$  (resp.  $\mathbf{u}$  and  $\mathbf{v}$ ) should be the moments of a measure  $\phi$  (resp.  $\varphi$  and  $\psi$ ). The constraint

$$L_{\mathbf{y}+\mathbf{u}}(\mathbf{x}^\alpha \omega^\beta) - L_{\mathbf{v}}(\mathbf{x}^\alpha p_\beta(\mathbf{a})) = 0, |\alpha + \deg(p_\beta)| \leq 2d,$$

is a necessary condition for  $\nu$  ( $:= \phi + \varphi$ )  $\leq \mathbf{T}^* \psi$ . Finally all the semidefinite constraints are necessary conditions for  $\text{support}(\phi) \subset \mathbf{K}$  (resp.  $\text{support}(\varphi) \subset \mathbf{X} \times \Omega$  and  $\text{support}(\psi) \subset \mathbf{X} \times \mathbf{A}$ ).

Therefore (4.5) is a *relaxation* of (3.5). Indeed, the truncated moments (up to order  $2d$ )  $(\mathbf{y}, \mathbf{v}, \mathbf{u})$  of  $(\phi, \psi, \mathbf{T}^* \psi - \phi)$  where  $(\phi, \psi)$  is an arbitrary feasible solution of (3.5), form a feasible solution of (4.5). Hence  $\rho_d \geq \rho$  for all  $d \geq d_0$ . Moreover,  $0 \leq \rho \leq \rho_{d+1} \leq \rho_d$  for all  $d \geq d_0$  and so (4.5) defines a *hierarchy* of semidefinite programs whose associated sequence of optimal values  $(\rho_d)_{d \geq d_0}$  is nonnegative and monotone non increasing.

4.2. **The dual of the semidefinite relaxations (4.5).** The dual of (4.5) is:

$$\begin{aligned}
(4.6) \quad \rho_d^* &= \inf_{h,w,\sigma_j^i} \int_{\mathbf{X}} w(\mathbf{x}) d\lambda(\mathbf{x}) : \\
&\text{s.t. } h(\mathbf{x}, \omega) - 1 = \sum_{j=0}^{m+1} \sigma_j^1 g_j + \sum_{\ell=1}^{\bar{s}} \sigma_\ell^1 s_\ell, \quad \forall(\mathbf{x}, \omega); \\
&h(\mathbf{x}, \omega) = \sum_{j=1}^m \sigma_j^2 g_j + \sum_{\ell=1}^{\bar{s}} \sigma_\ell^2 s_\ell, \quad \forall(\mathbf{x}, \omega); \\
&w(\mathbf{x}) - \sum_{\alpha,\beta} h_{\alpha\beta} \mathbf{x}^\alpha p_\beta(\mathbf{a}) = \sum_{j=1}^m \sigma_j^3 g_j + \sum_{\ell=1}^L \sigma_\ell^3 q_\ell, \quad \forall(\mathbf{x}, \mathbf{a}); \\
&\deg(h), \deg(w) \leq 2d; \sigma_j^1 \in \Sigma[\mathbf{x}, \omega]_{d-d_j}, j = 0, \dots, m+1, \\
&\sigma_j^2 \in \Sigma[\mathbf{x}, \omega]_{d-d_j}, \sigma_j^3 \in \Sigma[\mathbf{x}, \mathbf{a}]_{d-d_j}; j = 0, \dots, m, \\
&\sigma_\ell^3 \in \Sigma[\mathbf{x}, \mathbf{a}]_{d-d_\ell}, \ell = 1, \dots, L,
\end{aligned}$$

where  $h(\mathbf{x}, \omega) = \sum_{|\alpha+\beta| \leq 2d} h_{\alpha\beta} \mathbf{x}^\alpha \omega^\beta$ , and  $w(\mathbf{x}) = \sum_{|\alpha| \leq 2d} w_\alpha \mathbf{x}^\alpha$ .

The interpretation of (4.6) is clear. It is a reinforcement of the dual (3.6) in which the positivity constraints have been replaced with SOS *positivity certificates* à la Putinar. For instance, the positivity constraint “ $h \geq 1$  on  $\mathbf{K}$ ” in (3.6) becomes in (4.6) the stronger:

$$h(\mathbf{x}, \omega) - 1 = \sum_{j=0}^{m+1} \sigma_j^1 g_j + \sum_{\ell=1}^{\bar{s}} \sigma_\ell^1 s_\ell, \quad \forall(\mathbf{x}, \omega),$$

for some SOS polynomials  $(\sigma_j^1)$ .

**Theorem 4.2.** *Let Assumption 2.2 (and Assumption 2.3 as well if  $\Omega$  is unbounded) and assume that  $\mathbf{K}, \mathbf{A}, \mathbf{X} \times \Omega$  and  $\mathbf{X} \times \Omega \setminus \mathbf{K}$  all have nonempty interior. Then:*

(i) *Slater’s condition holds for (4.5) and so strong duality holds. That is, for every  $d \geq d_0$ ,  $\rho_d^* = \rho_d$  and (4.6) has an optimal solution  $(h_d, w_d)$ .*

(ii) *Next, define  $\mathbf{X}_\varepsilon^d := \{\mathbf{x} \in \mathbf{X} : w_d(\mathbf{x}) < \varepsilon\}$ . Then  $\mathbf{X}_\varepsilon^d \subset \mathbf{X}_\varepsilon^*$  for every  $d \geq d_0$ . In addition, if  $\lim_{d \rightarrow \infty} \rho_d = \rho$  then with  $\mathbf{x} \mapsto \kappa(\mathbf{x})$  as in Lemma 3.1:*

$$(4.7) \quad \lim_{d \rightarrow \infty} \|w_d(\mathbf{x}) - \kappa(\mathbf{x})\|_{L_1(\mathbf{X}, \lambda)} = 0 \quad \text{and} \quad \lim_{d \rightarrow \infty} \lambda(\mathbf{X}_\varepsilon^* \setminus \mathbf{X}_\varepsilon^d) = 0.$$

A proof is postponed to §7.3. Note that so far, optimal solutions of (4.6) provide us with a hierarchy of inner approximations  $\mathbf{X}_\varepsilon^d \subset \mathbf{X}_\varepsilon^*$ ,  $d \geq d_0$ . In addition, if the approximation scheme (4.5) (or (4.6)) is such that  $\lim_{d \rightarrow \infty} \rho_d = \rho$ , then Lemma 4.2 states that the inner approximations  $(\mathbf{X}_\varepsilon^d)$  have the additional strong asymptotic property (4.7) which in turn implies the highly desirable convergence result (4.7).

So to obtain (4.7) we need to ensure that  $\lim_{d \rightarrow \infty} \rho_d = \rho$  as  $d \rightarrow \infty$ .

**Theorem 4.3.** *Let Assumption 2.2 hold, and if  $\Omega$  is unbounded let Assumption 2.3 also hold. Consider the hierarchy of semidefinite programs (4.5) with associated monotone sequence of optimal values  $(\rho_d)_{d \geq d_0}$ . Then for each  $d \geq d_0$  there is an optimal solution  $(\mathbf{y}^d, \mathbf{u}^d, \mathbf{v}^d)$  and*

$$\rho_d = y_{00}^d \downarrow \phi^*(\mathbf{K}) = \rho, \quad \text{as } d \rightarrow \infty,$$

where  $\phi^*$  is part of an optimal solution  $(\phi^*, \psi^*)$  of (3.5).

A proof is postponed to §7.4.

**4.3. Accelerating convergence via Stokes.** In previous works of a similar flavor but for volume computation in [15] and [20, 27], it was observed that the convergence  $\rho_d \rightarrow \rho$  was rather slow. In our framework, by inspection of the dual (3.6), a potential slow convergence may arise as one tries to approximate from above a discontinuous function (the indicator function  $1_{\mathbf{K}}$  of a compact set  $\mathbf{K}$ ) by polynomials, and therefore one is faced with an annoying Gibb's phenomenon. The trick proposed in [15] resulted in a significant acceleration of the convergence but at the price of loosing its monotonicity (a highly desirable feature). This motivated the other strategy proposed in [20, 27], based on Stokes' theorem, which also resulted in a significantly faster convergence, but this time without loosing its monotonicity.

In this section we provide a means to accelerate the convergence  $\rho_d \rightarrow \rho$  in Theorem 4.3, also based on Stokes' theorem applied to the optimal solution  $\phi^*$  of (3.5). However, its implementation is much more complicated than in [20, 27] as it requires introducing an additional measure in the LP (3.5).

It works when the probability measures  $(\mu_{\mathbf{a}})_{\mathbf{a} \in \mathbf{A}}$ , satisfy some additional property: For all  $\mathbf{a} \in \mathbf{A}$ , either,

- $d\mu_{\mathbf{a}}(\omega) = s(\omega, \mathbf{a})$  for some polynomial  $s \in \mathbb{R}[\omega, \mathbf{a}]$ , or
- $d\mu_{\mathbf{a}}(\omega) = q_0(\mathbf{a}) s_1(\omega, \mathbf{a}) \exp(s_2(\omega, \mathbf{a})) d\omega$ , where  $q_0$  is a rational function and  $\omega \mapsto s_i(\omega, \mathbf{a})$  belongs to  $\mathbb{R}[\omega]$ ,  $i = 1, 2$ . In addition, for every fixed  $\mathbf{a}$ , and  $i = 1, \dots, p$ ,  $\partial s_2(\omega, \mathbf{a}) / \partial \omega_i$  is a rational function of  $\omega$ .

We detail the procedure for the case where  $\mathbf{\Omega} = \mathbb{R}$ ,  $\mathbf{a} = (a, \sigma) \in \mathbf{A} := [\underline{a}, \bar{a}] \times [\underline{\sigma}, \bar{\sigma}] \subset \mathbb{R}^2$ , and

$$d\mu_{\mathbf{a}}(\omega) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(\omega - a)^2}{2\sigma^2}\right) d\omega, \quad \mathbf{a} = (a, \sigma) \in \mathbf{A},$$

i.e.  $\mathcal{M}_{\mathbf{a}}$  is the family of all possible mixture of Gaussian probability measures on  $\mathbb{R}$  with mean  $a \in [\underline{a}, \bar{a}]$  and standard deviation  $\sigma \in [\underline{\sigma}, \bar{\sigma}]$ . Recall that  $\mathbf{K}_{\mathbf{x}} = \{\omega \in \mathbb{R} : f(\mathbf{x}, \omega) \leq 0\}$ . For every  $\mathbf{a} \in \mathbf{A}$ , and extended version of Stokes' theorem yields:

$$\int_{\mathbf{K}_{\mathbf{x}}} \frac{\partial (\omega^\beta f(\mathbf{x}, \omega) \exp(\frac{-(\omega - a)^2}{2\sigma^2}))}{\partial \omega} d\omega = 0, \quad \beta = 0, 1, \dots$$

for every  $\mathbf{x} \in \mathbf{S}$ . That is:

$$(4.8) \quad \int_{\mathbf{K}_{\mathbf{x}}} q_\beta(\mathbf{x}, \omega, \mathbf{a}) d\mu_{\mathbf{a}}(\omega) = 0, \quad \forall \mathbf{x} \in \mathbf{S}, \forall \beta = 0, 1, \dots,$$

where  $q_\beta \in \mathbb{R}[\mathbf{x}, \omega, \mathbf{a}]$  reads:

$$q_\beta(\mathbf{x}, \omega, \mathbf{a}) := \frac{\sigma^2 \partial (\omega^\beta f(\mathbf{x}, \omega))}{\partial \omega} - \omega^\beta f(\mathbf{x}, \omega) (\omega - a).$$

This in turn implies that for every  $\mathbf{a} \in \mathbf{A}$ ,

$$(4.9) \quad \int_{\mathbf{X}} \mathbf{x}^\alpha \left( \mathbf{a}^\gamma \int_{\mathbf{K}_{\mathbf{x}}} q_\beta(\mathbf{x}, \omega, \mathbf{a}) d\mu_{\mathbf{a}}(\omega) \right) d\lambda(\mathbf{x}) = 0,$$

for all  $\alpha \in \mathbb{N}^n$ ,  $\gamma \in \mathbb{N}^2$ , and  $\beta = 0, 1, \dots$ . In particular, with  $\mathbf{a}(\mathbf{x})$  as in Lemma 3.1:

$$\int_{\mathbf{X}} \mathbf{x}^\alpha \mathbf{a}(\mathbf{x})^\gamma \left( \int_{\mathbf{K}_{\mathbf{x}}} q_\beta(\mathbf{x}, \omega, \mathbf{a}(\mathbf{x})) d\mu_{\mathbf{a}(\mathbf{x})}(\omega) \right) d\lambda(\mathbf{x}) = 0,$$



or equivalently:

$$(4.10) \quad \int_{\mathbf{K}} \mathbf{x}^\alpha \mathbf{a}(\mathbf{x})^\gamma q_\beta(\mathbf{x}, \omega, \mathbf{a}(\mathbf{x})) d\phi^*(\mathbf{x}, \omega) = 0,$$

for all  $\alpha \in \mathbb{N}^n$ ,  $\gamma \in \mathbb{N}^2$ ,  $\beta = 0, 1, \dots$

Therefore in the infinite-dimensional LP (3.5) we may add the linear “generalized” moment constraints (4.10) because they are satisfied at an optimal solution  $\phi^*$ . However, the function  $(\mathbf{x}, \omega) \mapsto q_\beta(\mathbf{x}, \omega, \mathbf{a}(\mathbf{x}))$  is *not* a polynomial and these constraints cannot be implemented directly.

To overcome this problem introduce an additional measure  $\nu$  on  $\mathbf{K} \times \mathbf{A}$  and impose that its marginal  $\nu_{\mathbf{x}, \omega}$  on  $\mathbf{K}$  is  $\phi$  and its marginal  $\nu_{\mathbf{x}, \mathbf{a}}$  on  $\mathbf{X} \times \mathbf{A}$  is dominated by  $\psi$ . That is  $\nu_{\mathbf{x}, \omega} = \phi$  and  $\nu_{\mathbf{x}, \mathbf{a}} \leq \psi$ . We also need introduce the (Stokes) moment constraints:

$$(4.11) \quad \int_{\mathbf{X} \times \mathbf{A} \times \Omega} \mathbf{x}^\alpha \mathbf{a}^\gamma q_\beta(\mathbf{x}, \omega, \mathbf{a}) d\nu(\mathbf{x}, \omega, \mathbf{a}) = 0, \quad \forall (\alpha, \beta, \gamma) \in \mathbb{N}^n \times \mathbb{N}^p \times \mathbb{N}^2.$$

Recall that at an optimal solution  $(\phi^*, \psi^*)$  of (3.5),  $\hat{\psi}^*(d\mathbf{a}|\mathbf{x}) = \delta_{\mathbf{a}(\mathbf{x})}$  for all  $\mathbf{x} \in \mathbf{X}$  and so every feasible solution of the form  $(\phi^*, \psi^*, \nu)$  (hence with  $\nu_{\mathbf{x}, \omega} = \phi^*$  and  $\nu_{\mathbf{x}, \mathbf{a}} \leq \psi^*$ ) satisfies  $\hat{\nu}_{\mathbf{x}, \mathbf{a}}(d\mathbf{a}|\mathbf{x}) = \delta_{\mathbf{a}(\mathbf{x})}$  for all  $\mathbf{x} \in \text{supp}(\nu_{\mathbf{x}})$ , i.e., for all  $\mathbf{x} \in \text{supp}(\phi_{\mathbf{x}}^*)^3$ . Disintegrating  $\nu$  as  $\hat{\nu}(d\mathbf{a}|\mathbf{x}, \omega) d\nu_{\mathbf{x}, \omega}(\mathbf{x}, \omega)$  yields

$$\begin{aligned} 0 &= \int_{\mathbf{K}} \mathbf{x}^\alpha \left( \int_{\mathbf{A}} \mathbf{a}^\gamma q_\beta(\mathbf{x}, \omega, \mathbf{a}) \hat{\nu}(d\mathbf{a}|\mathbf{x}, \omega) \right) d\nu_{\mathbf{x}, \omega}(\mathbf{x}, \omega), \\ &= \int_{\mathbf{K}} \mathbf{x}^\alpha \mathbf{a}(\mathbf{x})^\gamma q_\beta(\mathbf{x}, \omega, \mathbf{a}(\mathbf{x})) d\nu_{\mathbf{x}, \omega}(\mathbf{x}, \omega), \\ &= \int_{\mathbf{K}} \mathbf{x}^\alpha \mathbf{a}(\mathbf{x})^\gamma q_\beta(\mathbf{x}, \omega, \mathbf{a}(\mathbf{x})) d\phi^*(\mathbf{x}, \omega), \quad \forall \alpha \in \mathbb{N}^n, \gamma \in \mathbb{N}^2, \beta \in \mathbb{N}, \end{aligned}$$

which is (4.10). So in the semidefinite relaxation (4.5), we introduce the additional vector  $\mathbf{z}^1 = (z_{\alpha, \beta, \gamma}^1)$  and  $\mathbf{z}^2 = (z_{\alpha, \gamma}^2)$ ,  $\alpha \in \mathbb{N}^n$ ,  $\beta \in \mathbb{N}^p$ ,  $\gamma \in \mathbb{N}^t$ , (ideally the respective moments of the measure  $\nu$  and  $\psi^* - \nu_{\mathbf{x}, \mathbf{a}}$  where  $\nu$  is described above), and the constraints

$$\begin{aligned} L_{\mathbf{z}^1}(\mathbf{x}^\alpha \omega^\beta) &= L_{\mathbf{y}}(\mathbf{x}^\alpha \omega^\beta), \quad \forall |\alpha| + |\beta| \leq 2d, \\ L_{\mathbf{z}^1}(\mathbf{x}^\alpha \mathbf{a}^\gamma) + L_{\mathbf{z}^2}(\mathbf{x}^\alpha \mathbf{a}^\gamma) &= L_{\mathbf{v}}(\mathbf{x}^\alpha \mathbf{a}^\gamma), \quad \forall |\alpha| + |\gamma| \leq 2d, \\ L_{\mathbf{z}^1}(\mathbf{x}^\alpha \mathbf{a}^\gamma q_\beta(\mathbf{x}, \omega, \mathbf{a})) &= 0 \quad \forall |\alpha| + |\gamma| + \deg(q_\beta) \leq 2d. \end{aligned}$$

Of course, for the same index  $d \in \mathbb{N}$ , the resulting semidefinite relaxation is more computationally demanding as it now includes moments of the measure  $\nu$  on  $\mathbf{X} \times \mathbf{A} \times \Omega$  (whereas in (4.5) we only have moments of measures on  $\mathbf{X} \times \Omega$  and  $\mathbf{X} \times \mathbf{A}$ ). However, being more constrained its optimal value can be significantly smaller and the resulting convergence  $\rho_d \rightarrow \rho$  as  $d$  increases, can be expected to be much faster.

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<sup>3</sup>This is because by compactness of  $\mathbf{X}$  and  $\mathbf{A}$ , for all  $\alpha, \gamma$ ,  $\int \mathbf{x}^\alpha \mathbf{a}^\gamma d\nu_{\mathbf{x}, \mathbf{a}}(\mathbf{x}, \mathbf{a}) = \int \mathbf{x}^\alpha \mathbf{a}(\mathbf{x})^\gamma \eta(\mathbf{x}, \mathbf{a}(\mathbf{x})) \lambda(d\mathbf{x})$  for some nonnegative measurable function  $\eta \leq 1$ , and so  $\nu_{\mathbf{x}}(d\mathbf{x}) = \int \eta(\mathbf{x}, \mathbf{a}(\mathbf{x})) \lambda(d\mathbf{x})$ . This in turn implies that for every  $\gamma$  and almost all  $\mathbf{x} \in \mathbf{X}$ ,  $\int \mathbf{a}^\gamma \hat{\nu}_{\mathbf{x}, \mathbf{a}}(d\mathbf{a}|\mathbf{x}) = \mathbf{a}(\mathbf{x})^\gamma = \int \mathbf{a}^\gamma \delta_{\mathbf{a}(\mathbf{x})}(d\mathbf{a})$ . Hence  $\hat{\nu}_{\mathbf{x}, \mathbf{a}}(d\mathbf{a}|\mathbf{x}) = \delta_{\mathbf{a}(\mathbf{x})}(d\mathbf{a})$  for all  $\mathbf{x} \in \text{supp}(\nu_{\mathbf{x}})$

Actually, in this framework of mixture of Gaussian measures, one may also replace (3.5) with:

$$(4.12) \quad \begin{aligned} \rho = \sup_{\phi, \psi \geq 0} \quad & \{ \phi(\mathbf{K} \times \mathbf{A}) : \phi_{\mathbf{x}, \omega} \leq \mathbf{T}^* \psi; \quad \phi_{\mathbf{x}, \mathbf{a}} \leq \psi; \quad \psi_{\mathbf{x}} = \lambda, \\ & \int_{\mathbf{K} \times \mathbf{A}} \mathbf{x}^\alpha \mathbf{a}^\gamma q_\beta(\mathbf{x}, \omega, \mathbf{a}) d\phi(\mathbf{x}, \mathbf{a}, \omega) = 0, \\ & \forall \alpha \in \mathbb{N}^n, \gamma \in \mathbb{N}^2, \beta \in \mathbb{N}^p; \\ & \phi \in \mathcal{M}_+(\mathbf{K} \times \mathbf{A}), \psi \in \mathcal{P}(\mathbf{X} \times \mathbf{A}) \}, \end{aligned}$$

where now  $\phi$  is a measure on  $\mathbf{K} \times \mathbf{A}$  (instead of  $\mathbf{K}$  before). The dual of (4.12) reads:

$$(4.13) \quad \begin{aligned} \rho^* = \inf_{w, h, \theta, s} \quad & \{ \int_{\mathbf{X}} w(\mathbf{x}) d\lambda(\mathbf{x}) : \\ & h(\mathbf{x}, \omega) + \theta(\mathbf{x}, \mathbf{a}) \\ & + \sum_{\alpha, \beta, \gamma} s_{\alpha\beta\gamma} \mathbf{x}^\alpha \mathbf{a}^\gamma q_\beta(\mathbf{x}, \mathbf{a}, \omega) \geq 1, \quad \text{on } \mathbf{K} \times \mathbf{A} \\ & w(\mathbf{x}) - Th(\mathbf{x}, \mathbf{a}) - \theta(\mathbf{x}, \mathbf{a}) \geq 0, \quad \text{on } \mathbf{X} \times \mathbf{A} \\ & h \geq 0 \text{ on } \mathbf{X} \times \Omega; \quad \theta \geq 0 \text{ on } \mathbf{X} \times \mathbf{A}, \\ & w \in \mathbb{R}[\mathbf{x}], h \in \mathbb{R}[\mathbf{x}, \omega], \theta \in \mathbb{R}[\mathbf{x}, \mathbf{a}], s \in \mathbb{R}[\mathbf{x}, \mathbf{a}, \omega] \}. \end{aligned}$$

In particular, let  $(w, h, \theta, s)$  be an arbitrary feasible solution of (4.13). Then for every  $\mathbf{x} \in \mathbf{X}$ , and with  $\mathbf{a}(\mathbf{x})$  as in Lemma 3.1,

$$\begin{aligned} w(\mathbf{x}) & \geq Th(\mathbf{x}, \mathbf{a}(\mathbf{x})) + \theta(\mathbf{x}, \mathbf{a}(\mathbf{x})) = \int_{\Omega} h(\mathbf{x}, \omega) d\mu_{\mathbf{a}(\mathbf{x})}(\omega) + \theta(\mathbf{x}, \mathbf{a}(\mathbf{x})) \\ & = \int_{\Omega} (h(\mathbf{x}, \omega) + \theta(\mathbf{x}, \mathbf{a}(\mathbf{x}))) d\mu_{\mathbf{a}(\mathbf{x})}(\omega) \\ & \geq \int_{\mathbf{K}_{\mathbf{x}}} (h(\mathbf{x}, \omega) + \theta(\mathbf{x}, \mathbf{a}(\mathbf{x}))) d\mu_{\mathbf{a}(\mathbf{x})}(\omega) \\ & = \int_{\mathbf{K}_{\mathbf{x}}} \underbrace{[h(\mathbf{x}, \omega) + \theta(\mathbf{x}, \mathbf{a}(\mathbf{x})) + \sum_{\alpha, \beta, \gamma} s_{\alpha\beta\gamma} \mathbf{x}^\alpha \mathbf{a}(\mathbf{x})^\gamma q_\beta(\mathbf{x}, \mathbf{a}(\mathbf{x}), \omega)]}_{\geq 1 \text{ on } \mathbf{K}_{\mathbf{x}}} d\mu_{\mathbf{a}(\mathbf{x})}(\omega) \\ & \quad - \sum_{\alpha, \beta, \gamma} s_{\alpha\beta\gamma} \mathbf{x}^\alpha \mathbf{a}(\mathbf{x})^\gamma q_\beta(\mathbf{x}, \mathbf{a}(\mathbf{x}), \omega) d\mu_{\mathbf{a}(\mathbf{x})}(\omega) \\ & \geq \int_{\mathbf{K}_{\mathbf{x}}} d\mu_{\mathbf{a}(\mathbf{x})} - \sum_{\alpha, \beta, \gamma} s_{\alpha\beta\gamma} \mathbf{x}^\alpha \mathbf{a}(\mathbf{x})^\gamma \underbrace{\int_{\mathbf{K}_{\mathbf{x}}} q_\beta(\mathbf{x}, \mathbf{a}(\mathbf{x}), \omega) d\mu_{\mathbf{a}(\mathbf{x})}(\omega)}_{= 0 \text{ by (4.8)}} \\ & \geq \kappa(\mathbf{x}). \end{aligned}$$

One may show that in (4.12) and (4.13),

$$\rho = \rho^* = \int_{\mathbf{X}} \kappa(\mathbf{x}) d\lambda(\mathbf{x}),$$

and (4.7) in Theorem 4.2 also holds for an arbitrary minimizing sequence of (4.13).

The hierarchy of associated SDP-relaxations (i.e. the analogues for (4.12) of (4.5) for (3.5)) and its dual hierarchy are obtained in an obvious manner by truncation of the infinite sequences. At step  $d$  of the latter hierarchy we also obtain a polynomial  $w_d$  with same properties as in Theorem 4.2

**4.4. Numerical experiments.** In the illustrative numerical experiments described below we have restricted to mixtures of univariate Gaussian variables  $\mu_{\mathbf{a}}$  (hence with  $\Omega = \mathbb{R}$  and  $\mathbf{a} = (\text{mean}, \text{deviation}) \in \mathbf{A} \subset \mathbb{R}^2$ ). To implement the semidefinite relaxations (4.12) we have used the GloptiPoly software [14] dedicated to solving the Generalized Moment Problem. The resulting SDPs are solved using version 8.1 of Mosek [30].

We discuss three examples chosen to a) illustrate the effect (and efficiency) of Stokes constraints, b) compare the approximations with the real feasible set  $\mathbf{X}_\varepsilon^*$  in (1.3) (approximated with intensive simulations), and c) show the behavior of the approximations for different violation probabilities.

**4.5. Approximations with and without Stokes.** In order to illustrate the difference in quality of the approximation of  $\mathbf{X}_\varepsilon^*$  when using or not using Stokes constraints, consider the example where  $\mathbf{X} = [-1, 1]$ ,  $f(\mathbf{x}, \omega) = \omega - \mathbf{x}$ ,  $\mathbf{A} = [-0.1, 0.1] \times [0.8, 1]$ , i.e., we consider univariate Gaussian measures with mean approximately 0 and deviation slightly less than 1. For every fixed  $\mathbf{x}$ , due to the simple expression of  $f$  we can express  $\text{Prob}_{\mu_{\mathbf{a}}}(\{\omega \in \Omega : g(\mathbf{x}, \omega) < 0\})$  as an analytic expression in  $\mathbf{a}$ . It is hence relatively easy to obtain a good estimation of  $\rho(\mathbf{x}) := \min_{\mathbf{a} \in \mathbf{A}} \text{Prob}_{\mu_{\mathbf{a}}}(\{\omega \in \Omega : g(\mathbf{x}, \omega) < 0\}) = 1 - \kappa(\mathbf{x})$  by sampling over  $\mathbf{a}$  and taking the minimum. In Figure 1 is displayed  $\mathbf{x} \mapsto \rho(\mathbf{x})$  in black and two different approximations  $w_d$  computed for relaxation orders  $d = 8$  in blue and  $d = 12$  in red. The dashed lines are the polynomials corresponding to problem formulations including Stokes constraints.

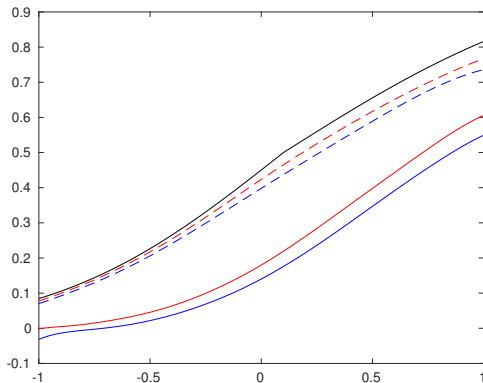


FIGURE 1. Approximation of  $\rho(\mathbf{x})$  (black) by polynomials  $1 - w_8(\mathbf{x})$  (blue) and  $1 - w_{12}(\mathbf{x})$  (red), dashed/solid lines correspond to with/without Stokes constraints

As a first remark observe that, in accordance with the theoretic results, all approximations are underestimators of  $\rho(\mathbf{x})$ . However, the approximations  $(1 - w_d)$  computed with Stokes constraints are much closer to  $\rho$  than the ones computed without. The former approximations are particularly close to  $\rho$  for significant values of violation probability, i.e., for small probabilities on the vertical axis. For higher probabilities they degrade (but are still quite good). This can be due to the non-differentiability of  $\rho$  at  $\mathbf{x} = 0.1$ . In order to display  $\mathbf{X}_\varepsilon^*$  and its  $\mathbf{X}_\varepsilon^d := \{\mathbf{x} \in \mathbf{X} :$

$w_d(\mathbf{x}) \leq \varepsilon$ , e.g., for a violation probability of 30% ( $\varepsilon = 0.3$ ) one looks at the sets  $\{\mathbf{x} \in \mathbf{X} : \rho(\mathbf{x}) \geq 0.7\}$  and  $\{\mathbf{x} \in \mathbf{X} : 1 - w_d(\mathbf{x}) \geq 0.7\}$  with  $w_d$  an optimal solution of the dual for the analogue of the step- $d$  relaxation of (4.12). This yields approximately that the interval  $[0.62, 1]$  is the true feasible set. With Stokes, the approximations  $w_8$  and  $w_{12}$  yield the respective intervals  $[0.85, 1]$  and  $[0.75, 1]$  while the approximations without Stokes provide an empty interval.

**4.6. Inner approximations from different relaxations.** As seen in the previous example, Stokes constraints are essential for the performance of our approach. In this section we therefore only report results using these additional constraints. In the second illustrative example,  $\mathbf{X} = [-1, 1]^2$ ,  $f(\mathbf{x}, \omega) = 2\omega \mathbf{x}_2^2 - 2\omega \mathbf{x}_1^2 - 1$  and mean and deviation as in the example before in an environment of 0 and 0.9 respectively. In Figure 2 we plot the feasible set  $\mathbf{X}_\varepsilon^*$  and its approximations ( $\mathbf{X}_\varepsilon^d$ ) for a violation level of 10% ( $\varepsilon = 0.1$ ).

The feasible set is approximated as follows. We discretize  $\mathbf{X}$  into 200 and  $\mathbf{A}$  into 100 steps in each direction respectively. For each point  $\mathbf{x}$  and each combination of parameters  $\mathbf{a}$  we draw 1000 realizations of  $\omega$  from the normal distribution described by  $\mathbf{a}$ . The point  $\mathbf{x}$  is considered to be feasible whenever for each  $\mathbf{a}$ ,  $f(\mathbf{x}, \omega)$  is positive for at least 900 out of the 1000 realizations of  $\omega$ . This simulation takes about 8600 seconds (without the authors claiming to be experts for Monte Carlo simulations) whereas the approximations for  $d = 8, 10, 12$  take 5, 43, and 482 seconds respectively.

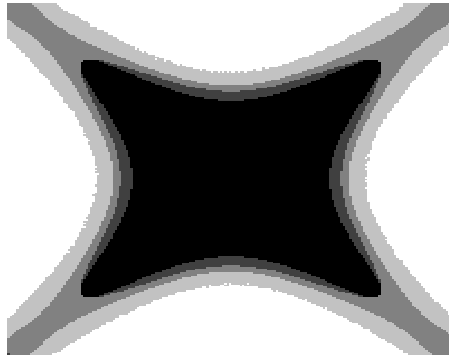


FIGURE 2. Monte Carlo simulation (light grey) of  $\mathbf{X}_\varepsilon^*$  and inner approximations  $\mathbf{X}_\varepsilon^d$  for  $d = 8, 10, 12$ , in decreasing intensity

Inspection of Figure 2 reveals that the feasible set  $\mathbf{X}_\varepsilon^*$  is non-convex. Already the lowest approximation  $\mathbf{X}_\varepsilon^8$  (black) is able to capture this behavior. The next approximation  $\mathbf{X}_\varepsilon^{10}$  (dark grey) is already a bit larger and  $\mathbf{X}_\varepsilon^{12}$  (medium grey) captures a significant part of  $\mathbf{X}_\varepsilon^*$  ( $\approx 74\%$ ). Its computation time is 18 times faster than the one required for the Monte Carlo simulation of  $\mathbf{X}_\varepsilon^*$ . In addition, and in contrast to the approximation via Monte Carlo,  $\mathbf{X}_\varepsilon^d$  is guaranteed to be inside the true feasible set.

$(r, \text{time}) \setminus \varepsilon$	50%	25%	12.5%	6.25%	3.125%
8 ( 30s)	96.94%	83.07%	69.70%	22.72%	0%
10 (107s)	99.91%	86.70%	73.21%	73.79%	2.48%
12 (633s)	100.0%	90.13%	79.94%	61.31%	27.98%

TABLE 1. Polynomial approximations vs Monte Carlo simulation.

**4.7. Inner approximations on different violation levels.** In the third example,  $\mathbf{X} = [-1, 1]^3$ ,  $\mathbf{\Omega} = \mathbb{R}$ ,  $f(\mathbf{x}, \omega) = -2\omega x_1^2 + 2\omega x_2^2 - 2\omega x_3^2 - 1$ . We compute the inner approximations  $\mathbf{X}_\varepsilon^d$  for  $d = 8, 10, 12$ . To compute the Monte Carlo approximation of  $\mathbf{X}_\varepsilon^*$  in a reasonable time, we fix the mean of the distribution to 0 and the standard deviation  $\sigma$  is taken in the interval  $\mathbf{A} = [0.4, 0.6]$ . For Monte Carlo we discretize  $\mathbf{X}$  and  $\mathbf{A}$  in 100 steps in each direction and draw again 1000 realizations of  $\omega$  for each point and each  $\sigma$ . This simulation takes about 2277 seconds. In the first example we have already seen that the polynomial approximations  $w_d$  are quite good for large violation probabilities. In Table 1 we compare the “volume” of our approximations against the Monte Carlo simulation, i.e. the ratio of the number of points admissible for our approximations over the number of points admissible in Monte Carlo. As the polynomial approximations are inner approximations, we expect the ratios to be less than one (assuming that Monte Carlo is accurate).

Again the polynomial approximations ( $w_d(x_1, x_2, x_3)$ ) are computed significantly faster than the Monte Carlo approximation  $\rho(x_1, x_2, x_3)$ . As in the first example, for large  $\varepsilon$  the approximations are pretty exact. However, for all relaxation orders  $d$  the quality of approximation decreases with  $\varepsilon$ , and eventually  $\mathbf{X}_{0.03125}^8 = \emptyset$ . However we should not forget that good approximations with small  $\varepsilon$  are difficult to achieve in any case. Therefore it is quite interesting that we can retrieve almost 30% of  $\mathbf{X}_{0.03125}^*$  with  $\mathbf{X}_{0.03125}^{12}$  and using moments up to order 12 only.

## 5. EXTENSION TO JOINT CHANCE-CONSTRAINTS

The case of *joint* chance-constraints, i.e., when several probabilistic constraints

$$(5.1) \quad \text{Prob}_\mu(f_j(\mathbf{x}, \omega) > 0, j = 1, \dots, s_f) > 1 - \varepsilon,$$

are considered jointly, is in general significantly more complicated than its relaxation which considers them individually, i.e.,

$$\text{Prob}_\mu(f_j(\mathbf{x}, \omega) > 0) > 1 - \varepsilon, \quad j = 1, \dots, s_f.$$

For instance, tractable formulations valid for individual chance-constraints may not be valid any more for joint chance-constraints.

We next show that joint chance-constraints (5.1) can be modelled in our framework, relatively easily. Instead of the set  $\mathbf{K}$  in (3.1) we now consider the sets:

$$(5.2) \quad \mathbf{K}^j := \{(\mathbf{x}, \omega) \in \mathbf{X} \times \Omega : f_j(\mathbf{x}, \omega) \leq 0\}, \quad j = 1, \dots, s_f.$$

$$(5.3) \quad \mathbf{K}_x^j := \{\omega \in \Omega : (\mathbf{x}, \omega) \in \mathbf{K}^j\}, \quad j = 1, \dots, s_f; \quad \forall \mathbf{x} \in \mathbf{X}$$

$$(5.4) \quad \mathbf{K} := \{(\mathbf{x}, \omega) \in \mathbf{X} \times \Omega : (\mathbf{x}, \omega) \in \bigcup_{j=1}^{s_f} \mathbf{K}^j\},$$

$$(5.5) \quad \mathbf{K}_x := \{\omega \in \Omega : (\mathbf{x}, \omega) \in \bigcup_{j=1}^{s_f} \mathbf{K}_x^j\}, \quad \forall \mathbf{x} \in \mathbf{X}$$

All results of §3, i.e. Theorem 3.2 and Theorem 3.3, remain valid with now  $\mathbf{K}$  and  $\mathbf{K}_x$ ,  $\mathbf{x} \in \mathbf{X}$ , as in (5.4) and (5.5) respectively. Indeed Lemma 3.1 remains valid with  $\mathbf{K}_x$  as (5.5). (In particular we still have  $\mu_{\mathbf{a}}(\partial \mathbf{K}_x) = 0$  for all  $\mathbf{a} \in \mathbf{A}$ , as now the boundary  $\partial \mathbf{K}_x$  is contained in a finite union of zero sets of polynomials.)

What is not obvious is how to define the analogues of the semidefinite relaxations (3.5) because  $\mathbf{K}$  is *not* a *basic* semi-algebraic set any more. It is a finite union  $\bigcup_{j=1}^{s_f} \mathbf{K}^j$  of basic semi-algebraic sets with overlaps.

The analogue of the infinite-dimensional LP (3.5) reads:

$$(5.6) \quad \hat{\rho} = \sup_{\phi_j, \psi \geq 0} \left\{ \sum_{j=1}^{s_f} \int_{\mathbf{K}^j} d\phi_j : \sum_{j=1}^{s_f} \phi_j \leq \mathbf{T}^* \psi; \quad \psi_x = \lambda, \right. \\ \left. \phi_j \in \mathcal{M}_+(\mathbf{K}^j), \psi \in \mathcal{P}(\mathbf{X} \times \mathbf{A}) \right\},$$

where  $\mathbf{T}^*$  is defined in Lemma 2.6. It is important to emphasize that even though the sets  $\mathbf{K}^j$  overlap, we do *not* require that the measures  $\phi_j$  are mutually singular.

The dual of (5.6) reads:

$$(5.7) \quad \hat{\rho}^* = \inf_{h, w} \left\{ \int_{\mathbf{X}} w d\lambda : \quad h(\mathbf{x}, \omega) \geq 1 \quad \text{on } \mathbf{K}^j, j = 1, \dots, s_f \right. \\ \left. w(\mathbf{x}) - \mathbf{T}h(\mathbf{x}, \mathbf{a}) \geq 0 \quad \text{on } \mathbf{X} \times \mathbf{A}; \quad h \geq 0 \text{ on } \mathbf{X} \times \Omega, \right. \\ \left. w \in \mathbb{R}[\mathbf{x}]; h \in \mathbb{R}[\mathbf{x}, \omega] \right\}.$$

**Theorem 5.1.** *Let  $\mathbf{K}^j$ ,  $j = 1, \dots, s_f$ , and  $\mathbf{K}$  be as in (5.2) and (5.4) respectively. Then:*

- (i) *The optimal value  $\rho$  of (3.5) and the optimal value  $\hat{\rho}$  of (5.6) are identical.*
- (ii) *Define the functions:*

$$(5.8) \quad (\mathbf{x}, \omega) \mapsto \theta_j(\mathbf{x}, \omega) := \frac{1}{|\{\ell \in \{1, \dots, s_f\} : (\mathbf{x}, \omega) \in \mathbf{K}_\ell\}|}, \quad j = 1, \dots, s_f,$$

and let  $(\phi^*, \psi^*)$  be an optimal solution of (5.6). Then  $(\phi_1^*, \dots, \phi_{s_f}^*, \psi^*)$  with

$$(5.9) \quad d\phi_j^*(\mathbf{x}, \omega) := \mathbf{1}_{\mathbf{K}^j}(\mathbf{x}, \omega) \theta_j(\mathbf{x}, \omega) d\phi^*(\mathbf{x}, \omega), \quad j = 1, \dots, s_f,$$

is an optimal solution of (5.6) and  $\phi^* = \sum_j \phi_j^*$ .

*Proof.* Let  $(\phi_1, \dots, \phi_{s_f}, \psi)$  be an arbitrary feasible solution of (5.6) and let  $\phi := \sum_{j=1}^{s_f} \phi_j$ . Then  $\phi \in \mathcal{M}(\mathbf{K})_+$  and  $\phi \leq \mathbf{T}^* \psi$ . Therefore  $(\phi, \psi)$  is feasible for (3.5).

Morover, as  $\text{supp}(\phi_j) \subset \mathbf{K}^j \subset \mathbf{K}$  for all  $j = 1, \dots, s_f$ ,

$$\sum_{j=1}^{s_f} \int_{\mathbf{K}^j} d\phi_j = \sum_{j=1}^{s_f} \int_{\mathbf{K}} d\phi_j = \int_{\mathbf{K}} d\left(\sum_{j=1}^{s_f} \phi_j\right) = \int_{\mathbf{K}} d\phi = \phi(\mathbf{K}),$$

which shows that  $\hat{\rho} \leq \rho$ . To prove the reverse inequality consider the functions  $(\theta_j)$  in (5.8), and let  $(\phi^*, \psi^*) \in \mathcal{M}_+(\mathbf{K}) \times \mathcal{M}_+(\mathbf{X} \times \mathbf{A})$  be an optimal solution of (3.5). Observe that

$$\sum_{j=1}^{s_f} \theta_j(\mathbf{x}, \omega) = 1, \quad \forall (\mathbf{x}, \omega) \in \mathbf{K}.$$

Let  $(\phi_j^*)$ ,  $j := 1, \dots, s_f$ , be as in (5.9). Then  $\phi_j^* \in \mathcal{M}_+(\mathbf{K}_j)$ ,  $j = 1, \dots, s_f$ , and  $\sum_{j=1}^{s_f} \phi_j^*(\mathbf{K}_j) = \phi^*(\mathbf{K})$ . Hence  $\rho \leq \hat{\rho}$ . Therefore  $(\phi_1^*, \dots, \phi_{s_f}^*, \psi^*)$  is an optimal solution of (5.6) and  $\phi^* = \sum_j \phi_j^*$ .  $\square$

As a consequence of Theorem 5.1, Theorem 3.3 also holds with now  $\mathbf{K}_x$  as in (5.5). In the original proof just use  $\phi = \sum_j \phi_j$  and the definitions of  $\mathbf{K}$  and  $\mathbf{K}_x$  in (5.4)-(5.5).

**5.1. Semidefinite relaxations.** We briefly describe the semidefinite relaxations of the LP (5.6), which are the analogues of (4.5) for the LP (3.5). For every  $j = 1, \dots, s_f$  let  $g_j^* := -f_j$ . Let  $2d_0$  to be the largest degree appearing in the polynomials that describe  $\mathbf{K}, \Omega, \mathbf{A}$ , and consider the semidefinite programs indexed by  $d \geq d_0$ .

$$(5.10) \quad \begin{aligned} \rho_d = & \sup_{\mathbf{y}^j, \mathbf{u}, \mathbf{v}} \sum_{j=1}^{s_f} y_{00}^j \\ \text{s.t. } & L_{\mathbf{y}^1 + \dots + \mathbf{y}^{s_f} + \mathbf{u}}(\mathbf{x}^\alpha \omega^\beta) - L_{\mathbf{v}}(\mathbf{x}^\alpha p_\beta(\mathbf{a})) = 0, \quad |\alpha + \deg(p_\beta)| \leq 2d, \\ & L_{\mathbf{v}}(\mathbf{x}^\alpha) = \lambda_\alpha, \quad \alpha \in \mathbb{N}_{2d}^n, \\ & \mathbf{M}_d(\mathbf{y}^j), \mathbf{M}_d(\mathbf{u}), \mathbf{M}_d(\mathbf{v}) \succeq 0, \\ & \mathbf{M}_{d-d_{m+1}}(g_j^* \mathbf{y}^j) \succeq 0, \quad j = 1, \dots, s_f, \\ & \mathbf{M}_{d-d_\ell}(g_\ell \mathbf{y}^j), \mathbf{M}_{d-d_\ell}(g_\ell \mathbf{u}), \mathbf{M}_d(g_\ell \mathbf{v}) \succeq 0, \\ & \ell = 1, \dots, m; \quad j = 1, \dots, s_f, \\ & \mathbf{M}_{d-d'_\ell}(s_\ell \mathbf{y}^j), \mathbf{M}_{d-d'_\ell}(s_\ell \mathbf{u}) \succeq 0, \\ & \ell = 1, \dots, \bar{s}; \quad j = 1, \dots, s_f, \\ & \mathbf{M}_{d-d'_\ell}(q_\ell \mathbf{v}) \succeq 0, \quad \ell = 1, \dots, L, \end{aligned}$$

where  $\mathbf{y}^j = (y_{\alpha\beta}^j)$ ,  $\mathbf{u} = (v_{\alpha\beta})$ ,  $(\alpha, \beta) \in \mathbb{N}^n \times \mathbb{N}^p$ ,  $j = 1, \dots, s_f$ , and  $\mathbf{v} = (v_{\alpha\eta})$ ,  $(\alpha, \eta) \in \mathbb{N}^n \times \mathbb{N}^t$ .

For every  $d \geq d_0$ ,  $\rho_d \geq \hat{\rho}$  ( $= \rho$ ) and Theorem 4.3 is valid for the hierarchy of semidefinite relaxations (5.10). Next, under the same assumptions of non-empty interior for  $\mathbf{X}, \mathbf{A}, \Omega, \mathbf{K}, \mathbf{K}^j$  and  $\mathbf{X} \times \Omega \setminus \mathbf{K}$ , Theorem 4.2 is also valid for the dual hierarchy associated with (5.10), the analogue of (4.6).

## 6. CONCLUSION

Computing or even approximating the feasible set associated with a distributionally-robust chance-constraint is a challenging problem. We have described a systematic

numerical scheme which provides a monotone sequence (a hierarchy) of inner approximations, all in the form  $\{\mathbf{x} \in \mathbf{X} : w_d(\mathbf{x}) < \varepsilon\}$  for some polynomial of increasing degree  $d$ , with strong asymptotic guarantees as  $d$  increases. To the best of our knowledge it is the first result of this type at this level of generality. Of course this comes with a price as the polynomial which defines each approximation is obtained by solving a semidefinite program whose size increases with its degree. Therefore and so far, this approach is limited to problems of small dimension (except perhaps if some sparsity can be exploited). So in its present form this contribution should be considered as complementary (rather than a competitor) to other algorithmic approaches where scalability is of primary importance. However it may also provide useful insights and a benchmark (for small dimension problems) for the latter approaches.

## 7. APPENDIX

**Lemma 7.1.** *Under Assumption 2.3, every  $\mu \in \mathcal{M}_{\mathbf{a}}$  is moment determinate.*

*Proof.* As  $\mu \in \mathcal{M}_{\mathbf{a}}$ , there exists  $\varphi \in \mathcal{P}(\mathbf{A})$  such that

$$\mu(B) = \int_{\Omega} \mu_{\mathbf{a}}(B) d\varphi(\mathbf{a}), \quad B \in \mathcal{B}(\Omega).$$

By Assumption 2.3, there exists  $c, \gamma$  such that for every  $i = 1, \dots, p$ ,

$$\int_{\Omega} \exp(c|\omega_i|) d\mu_{\mathbf{a}}(\omega) < \gamma, \quad \forall \mathbf{a} \in \mathbf{A},$$

and therefore

$$\sup_{i=1, \dots, p} \int_{\Omega} \exp(c|\omega_i|) d\mu(\omega) < \gamma.$$

As  $(c\omega_i)^{2j}/(2j)! < \exp(|\omega_i|)$ , one obtains  $\int_{\Omega} \omega_i^{2j} d\mu(\omega) < c^{-2j}\gamma(2j)!$  for all  $j = 1, 2, \dots$  and all  $i = 1, \dots, p$ . But this implies

$$\sum_{i=1}^{\infty} \left( \int_{\Omega} \omega_i^{2j} d\mu(\omega) \right)^{-1/2j} = +\infty, \quad i = 1, \dots, p,$$

that is,  $\mu$  satisfies Carleman's condition (2.1), and so is moment determinate.  $\square$

### 7.1. Proof of Theorem 3.3.

*Proof.* *Weak duality* holds because for every feasible solution  $(w, h)$  of (3.6) and  $(\phi, \psi)$  of (3.5), one has:

$$\begin{aligned} \int_{\mathbf{X}} w d\lambda &= \int_{\mathbf{X} \times \mathbf{A}} w(\mathbf{x}) d\psi(\mathbf{x}, \mathbf{a}) \geq \int_{\mathbf{X} \times \mathbf{A}} \mathbf{T}h(\mathbf{x}, \mathbf{a}) d\psi(\mathbf{x}, \mathbf{a}) \\ &= \int_{\mathbf{X} \times \Omega} h(\mathbf{x}, \omega) \mathbf{T}^* \psi(d(\mathbf{x}, \omega)) \\ &\geq \int_{\mathbf{K}} h(\mathbf{x}, \omega) d\phi(\mathbf{x}, \omega) \\ &\geq \int_{\mathbf{K}} d\phi = \phi(\mathbf{K}). \end{aligned}$$



Moreover let  $\psi^*$  be an optimal solution of (3.5) as in Theorem 3.2, so that  $\psi^* = \delta_{\mathbf{a}(\mathbf{x})} \lambda(d\mathbf{x})$ . Then for every  $\mathbf{x} \in \mathbf{X}$ :

$$\begin{aligned} w(\mathbf{x}) &\geq \int_{\mathbf{A}} \mathbf{T}h(\mathbf{x}, \mathbf{a}) \psi^*(d\mathbf{a}|\mathbf{x}) = \int_{\Omega} h(\mathbf{x}, \omega) d\mu_{\mathbf{a}(\mathbf{x})}(\omega) \\ &\geq \int_{\mathbf{K}_{\mathbf{x}}} h(\mathbf{x}, \omega) d\mu_{\mathbf{a}(\mathbf{x})}(\omega) \\ &\geq \int_{\mathbf{K}_{\mathbf{x}}} d\mu_{\mathbf{a}(\mathbf{x})}(\omega) = \kappa(\mathbf{x}) \end{aligned}$$

i.e.,  $w(\mathbf{x}) \geq \kappa(\mathbf{x})$  for all  $\mathbf{x} \in \mathbf{X}$ . In particular

$$\{\mathbf{x} \in \mathbf{X} : w(\mathbf{x}) < \varepsilon\} \subset \{\mathbf{x} \in \mathbf{X} : \kappa(\mathbf{x}) < \varepsilon\} = \mathbf{X}_{\varepsilon}^*.$$

Next, if there is no duality gap, i.e. if  $\rho = \rho^*$ , then for a minimizing sequence  $(w_n, h_n)$  of (3.6),

$$\lim_{n \rightarrow \infty} \int_{\mathbf{X}} (w_n(\mathbf{x}) - \kappa(\mathbf{x})) d\lambda(\mathbf{x}) = \rho^* - \rho = 0,$$

that is,  $w_n$  converges to  $\kappa(\mathbf{x})$  in  $L_1(\mathbf{X}, \lambda)$ . Finally, by Ash [3, Theorem 2.5.1], convergence in  $L_1(\mathbf{X}, \lambda)$  implies convergence in  $\lambda$ -measure, and so, for every fixed  $0 < \ell \in \mathbb{N}$ ,

$$(7.1) \quad \lim_{n \rightarrow \infty} \lambda\{\mathbf{x} \in \mathbf{X} : |w_n(\mathbf{x}) - \kappa(\mathbf{x})| > 1/\ell\} = 0.$$

Next, observe that

$$\mathbf{X}_{\varepsilon}^* = \{\mathbf{x} \in \mathbf{X} : \kappa(\mathbf{x}) < \varepsilon\} = \bigcup_{\ell=1}^{\infty} \underbrace{\{\mathbf{x} \in \mathbf{X} : \kappa(\mathbf{x}) < \varepsilon - 1/\ell\}}_{:=R_{\ell}}$$

and so  $\lambda(\mathbf{X}_{\varepsilon}^*) = \lim_{\ell \rightarrow \infty} \lambda(R_{\ell})$ . Next

$$\lambda(R_{\ell}) = \lambda(R_{\ell} \cap \{\mathbf{x} : w_n(\mathbf{x}) < \varepsilon\}) + \lambda(R_{\ell} \cap \{\mathbf{x} : w_n(\mathbf{x}) \geq \varepsilon\}).$$

By convergence in measure (7.1),  $\lim_{n \rightarrow \infty} \lambda(R_{\ell} \cap \{\mathbf{x} : w_n(\mathbf{x}) \geq \varepsilon\}) = 0$ . Hence

$$\lambda(R_{\ell}) = \lim_{n \rightarrow \infty} \lambda(R_{\ell} \cap \{\mathbf{x} : w_n(\mathbf{x}) < \varepsilon\}) \leq \lim_{n \rightarrow \infty} \lambda(\{\mathbf{x} : w_n(\mathbf{x}) < \varepsilon\}) \leq \lambda(\mathbf{X}_{\varepsilon}^*),$$

and as  $\lambda(R_{\ell}) \rightarrow \lambda(\mathbf{X}_{\varepsilon}^*)$ ,  $\lim_{n \rightarrow \infty} \lambda(\{\mathbf{x} : w_n(\mathbf{x}) < \varepsilon\}) = \lambda(\mathbf{X}_{\varepsilon}^*)$ .  $\square$

## 7.2. Proof of Lemma 4.1.

*Proof.* If  $\Omega$  is compact then it follows from the definition of  $\mathbf{T}$  and  $\mathbf{T}^*$ . For the general case where  $\Omega$  is not necessarily compact, disintegrate  $\nu$  and  $\psi$  as

$$d\nu(\mathbf{x}, \Omega) = \hat{\nu}(d\omega|\mathbf{x}) \nu_{\mathbf{x}}(d\mathbf{x}), \quad d\psi(\mathbf{x}, \mathbf{a}) = \hat{\psi}(d\mathbf{a}|\mathbf{x}) \psi_{\mathbf{x}}(d\mathbf{x}).$$

By (4.1) with  $\beta = 0$ ,  $\int_{\mathbf{X}} \mathbf{x}^{\alpha} \nu_{\mathbf{x}}(d\mathbf{x}) = \int_{\mathbf{X}} \mathbf{x}^{\alpha} \psi_{\mathbf{x}}(d\mathbf{x})$  for all  $\alpha \in \mathbb{N}^n$ , and as  $\mathbf{X}$  is compact it follows that  $\psi_{\mathbf{x}} = \nu_{\mathbf{x}}$ . Next, fix  $\beta \in \mathbb{N}^p$ . Then for every  $\alpha \in \mathbb{N}^n$

$$\int_{\mathbf{X}} \mathbf{x}^{\alpha} \left( \int_{\Omega} \omega^{\beta} \hat{\nu}(d\omega|\mathbf{x}) \right) \nu_{\mathbf{x}}(d\mathbf{x}) = \int_{\mathbf{X}} \mathbf{x}^{\alpha} \left( \int_{\mathbf{A}} p_{\beta}(\mathbf{a}) \hat{\psi}(d\mathbf{a}|\mathbf{x}) \right) \nu_{\mathbf{x}}(d\mathbf{x}),$$

and again as  $\mathbf{X}$  is compact this implies

$$\int_{\Omega} \omega^{\beta} \hat{\nu}(d\omega|\mathbf{x}) = \int_{\mathbf{A}} p_{\beta}(\mathbf{a}) \hat{\psi}(d\mathbf{a}|\mathbf{x}), \quad \forall \mathbf{x} \in \mathbf{X} \setminus B_{\beta},$$

where  $B_\beta \in \mathcal{B}(\mathbf{X})$  is such that  $\nu_{\mathbf{x}}(B_\beta) = 0$ . As  $\beta \in \mathbb{N}^p$  was arbitrary,

$$\int_{\Omega} \omega^\beta \hat{\nu}(d\omega|\mathbf{x}) = \int_{\mathbf{A}} p_\beta(\mathbf{a}) \hat{\psi}(d\mathbf{a}|\mathbf{x}), \quad \forall \beta \in \mathbb{N}^p, \forall \mathbf{x} \in \mathbf{X} \setminus B^*,$$

where  $\nu_{\mathbf{x}}(B^*) = \nu_{\mathbf{x}}(\bigcup_{\beta} B_\beta) = 0$ . Next, define the measure  $\varphi_{\mathbf{x}}$  on  $\Omega$  by

$$\varphi_{\mathbf{x}}(B) = \int_{\mathbf{A}} \mu_{\mathbf{a}}(B) \hat{\psi}(d\mathbf{a}|\mathbf{x}), \quad \forall \mathbf{x} \in \mathbf{X} \setminus B^*,$$

which is well defined by Assumption 2.2(i). Moreover by construction,  $\varphi_{\mathbf{x}} \in \mathcal{M}_{\mathbf{a}}$  for all  $\mathbf{x} \in \mathbf{X} \setminus B^*$ , and

$$\begin{aligned} \int_{\Omega} \omega^\beta \hat{\nu}(d\omega|\mathbf{x}) &= \int_{\mathbf{A}} p_\beta(\mathbf{a}) \hat{\psi}(d\mathbf{a}|\mathbf{x}), \quad \forall \beta \\ &= \int_{\mathbf{A}} \left( \int_{\Omega} \omega^\beta \mu_{\mathbf{a}}(d\omega) \right) \hat{\psi}(d\mathbf{a}|\mathbf{x}), \quad \forall \beta \\ &= \int_{\Omega} \omega^\beta \varphi_{\mathbf{x}}(d\omega), \quad \forall \beta. \end{aligned}$$

By Lemma 7.1,  $\varphi_{\mathbf{x}}$  is moment determinate and therefore  $\hat{\nu}(d\omega|\mathbf{x}) = \varphi_{\mathbf{x}}$  for all  $\mathbf{x} \in \mathbf{X} \setminus B^*$ . Next, let  $g \in \mathcal{B}(\mathbf{X} \times \Omega)$  be fixed arbitrary. Then:

$$\begin{aligned} \langle g, \nu \rangle &= \langle g, \hat{\nu}(d\omega|\mathbf{x}) \nu_{\mathbf{x}}(d\mathbf{x}) \rangle = \langle g, \varphi_{\mathbf{x}}(d\omega) \nu_{\mathbf{x}}(d\mathbf{x}) \rangle \\ &= \langle g, \varphi_{\mathbf{x}}(d\omega) \psi_{\mathbf{x}}(d\mathbf{x}) \rangle \\ &= \langle \mathbf{T}g, \hat{\psi}(d\mathbf{a}|\mathbf{x}) \psi_{\mathbf{x}}(d\mathbf{x}) \rangle \\ &= \langle \mathbf{T}g, \psi \rangle = \langle g, \mathbf{T}^* \psi \rangle, \end{aligned}$$

and as it holds for all  $g \in \mathcal{B}(\mathbf{X} \times \Omega)$ ,  $\nu = \mathbf{T}^* \psi$ .  $\square$

### 7.3. Proof of Theorem 4.2.

*Proof.* (i) We first prove that Slater's condition holds for (4.5). Observe that for all feasible solutions,  $y_{00} + u_{00} = L_{\mathbf{v}}(1) = 1$  and therefore  $0 \leq \rho_d \leq 1$ . Let  $\lambda_{\mathbf{A}}$  be the Lebesgue measure on  $\mathbf{A}$ , normalized to a probability measure. Let  $\mathbf{y}$  be the the moments of the measure  $d\phi(\mathbf{x}, \omega) = \mathbf{1}_{\mathbf{S}}(\mathbf{x}) d\lambda(\mathbf{x}) \otimes \hat{\mu}(d\omega)$ , where

$$\hat{\mu}(B) = \int_{\mathbf{A}} \mu_{\mathbf{a}}(B) d\lambda_{\mathbf{A}}(\mathbf{a}), \quad B \in \mathcal{B}(\Omega).$$

Similarly, let  $\nu := \lambda \otimes \hat{\mu}$  (and so  $\phi \leq \nu$ ) and let  $\psi = \lambda_{\mathbf{A}} \otimes \lambda$ . Let  $\mathbf{y}$  (resp.  $\mathbf{u}$ ) be the vector of moments of  $\phi$  (resp.  $\nu - \phi$ ) up to order  $2d$ , and let  $\mathbf{v}$  be the vector of moments of  $\psi$  up to order  $2d$ . Then  $\mathbf{M}_d(\mathbf{y}), \mathbf{M}_d(\mathbf{u}), \mathbf{M}_d(\mathbf{v}) \succ 0$ . Similarly  $\mathbf{M}_{d-d_j}(\mathbf{y}) \succ 0$ ,  $j = 0, \dots, m$ ,  $\mathbf{M}_{d-d_j}(g_j \mathbf{u}) \succ 0$ ,  $j = 1, \dots, m$ , and  $\mathbf{M}_{d-d_\ell}^i(q_\ell \mathbf{v}) \succ 0$ ,  $\ell = 1, \dots, L$ , because  $\mathbf{X} \times \Omega, \mathbf{K}, \mathbf{X} \times \Omega \setminus \mathbf{K}, \mathbf{A}$  all have nonempty interior. Moreover, as

$$\begin{aligned} \int \mathbf{x}^\alpha \omega^\beta d\nu(\mathbf{x}, \omega) &= \int_{\mathbf{X}} \mathbf{x}^\alpha d\lambda(\mathbf{x}) \int_{\mathbf{A}} \left( \int_{\Omega} \omega^\beta d\mu_{\mathbf{a}}(\omega) \right) d\lambda_{\mathbf{A}}(\mathbf{a}) \\ &= \int_{\mathbf{X}} \mathbf{x}^\alpha d\lambda(\mathbf{x}) \int_{\mathbf{A}} p_\beta(\mathbf{a}) d\lambda_{\mathbf{A}}(\mathbf{a}) = \int_{\mathbf{X} \times \mathbf{A}} \mathbf{x}^\alpha p_\beta(\mathbf{a}) d\psi(\mathbf{x}, \mathbf{a}), \end{aligned}$$

we deduce  $L_{\mathbf{y}+\mathbf{u}}(\mathbf{x}^\alpha \omega^\beta) = L_{\mathbf{v}}(\mathbf{x}^\alpha p_\beta(\mathbf{a}))$ , and therefore  $(\mathbf{y}, \mathbf{u}, \mathbf{v})$  is an admissible solution of (4.5) which is strictly feasible, i.e., Slater's condition holds for (4.5) and therefore strong duality  $\rho_d = \rho_d^*$  holds. In particular, as  $\rho_d < \infty$ , (4.6) has an optimal solution  $(h_d, w_d, \sigma_j^i)$ .

(ii) Next feasibility in (4.6) implies

$$\begin{aligned} h_d(\mathbf{x}, \omega) &\geq 1, \quad \forall (\mathbf{x}, \omega) \in \mathbf{K}, \\ h_d(\mathbf{x}, \omega) &\geq 0, \quad \forall (\mathbf{x}, \omega) \in \mathbf{X} \times \Omega, \\ w_d(\mathbf{x}) - \sum_{\alpha, \beta} h_{d, \alpha, \beta} \mathbf{x}^\alpha p_\beta(\mathbf{a}) &\geq 0, \quad \forall (\mathbf{x}, \mathbf{a}) \in \mathbf{X} \times \mathbf{A}. \end{aligned}$$

Let  $(\phi^*, \psi^*)$  be optimal solution of (3.5), as in Theorem 3.2, and let  $d\nu^*(\mathbf{x}, \omega) : \mu_{\mathbf{a}(\mathbf{x})}(d\omega) \lambda(d\mathbf{x})$ . Let  $\mathbf{x} \in \mathbf{X}$  be fixed. Integrating the first w.r.t.  $\nu_{\mathbf{x}}^*(d\omega|\mathbf{x}) (= \mu_{\mathbf{a}(\mathbf{x})}(d\omega))$ , the third one w.r.t.  $\psi^*(d\mathbf{a}|\mathbf{x}) (= \delta_{\mathbf{a}(\mathbf{x})})$ , and using the second inequality yields:

$$\begin{aligned} w_d(\mathbf{x}) + \sum_{\alpha, \beta} h_{d, \alpha, \beta} \mathbf{x}^\alpha \left( \int_{\Omega} \omega^\beta d\mu_{\mathbf{a}(\mathbf{x})}(\omega) - \underbrace{\int_{\mathbf{A}} p_\beta(\mathbf{a}) d\psi^*(d\mathbf{a}|\mathbf{x})}_{=\int_{\Omega} \omega^\beta d\mu_{\mathbf{a}(\mathbf{x})}(\omega)} \right) \\ \geq \begin{cases} \int_{\mathbf{K}_{\mathbf{x}}} \nu_{\mathbf{x}}^*(d\omega|\mathbf{x}) = \kappa(\mathbf{x}), & \text{if } \mathbf{K}_{\mathbf{x}} \neq \emptyset, \\ 0 (= \kappa(\mathbf{x})) & \text{otherwise.} \end{cases} \end{aligned}$$

In other words

$$(7.2) \quad w_d(\mathbf{x}) \geq \kappa(\mathbf{x}), \quad \forall \mathbf{x} \in \mathbf{X}.$$

Therefore

$$\{\mathbf{x} \in \mathbf{X} : w_d(\mathbf{x}) < \varepsilon\} \subseteq \{\mathbf{x} \in \mathbf{X} : \kappa(\mathbf{x}) < \varepsilon\} = \mathbf{X}_\varepsilon^*.$$

Next if  $\lim_{d \rightarrow \infty} \rho_d = \rho$  then

$$\lim_{d \rightarrow \infty} \int_{\mathbf{X}} w_d d\lambda = \lim_{d \rightarrow \infty} \rho_d^* = \lim_{d \rightarrow \infty} \rho_d = \int_{\mathbf{X}} \kappa(\mathbf{x}) \lambda(d\mathbf{x}),$$

which yields

$$\int_{\mathbf{X}} (w_d(\mathbf{x}) - \kappa(\mathbf{x})) d\lambda(\mathbf{x}) \rightarrow 0 \quad \text{as } d \rightarrow \infty,$$

which combined with (7.2), yields  $w_d \rightarrow \kappa$  in  $L_1(\mathbf{X}, \lambda)$ .  $\square$

#### 7.4. Proof of Theorem 4.3.

*Proof.* We prove Theorem 4.3 for the case where  $\Omega$  is unbounded as the arguments also work for the bounded case (but without Assumption 2.2 and 2.3).

Let  $(\mathbf{y}^k, \mathbf{u}^k, \mathbf{v}^k)$  be a maximizing sequence of (4.5). For every  $i = 1, \dots, p$  and  $j \in \mathbb{N}$ , let  $\beta(i, j) \in \mathbb{N}^p$  be such that  $\beta(i, j)_k = 2^j \delta_{k=i}$ . Observe that for every feasible solution  $(\mathbf{y}, \mathbf{u}, \mathbf{v})$  of (4.5), and from a consequence of Assumption 2.3 (see the proof of Lemma 7.1):

$$(7.3) \quad \begin{aligned} L_{\mathbf{y}}(\omega_i^{2^j}) + L_{\mathbf{u}}(\omega_i^{2^j}) &= L_{\mathbf{v}}(p_{\beta(i, j)}(\mathbf{a})) \\ &= \int_{\mathbf{A}} p_{\beta(i, j)}(\mathbf{a}) d\lambda_{\mathbf{A}}(\mathbf{a}) \leq c^{-2^j} \gamma(2^j)! \end{aligned}$$

for all  $j = 1, \dots, d$  and all  $i = 1, \dots, p$ . Therefore  $L_{\mathbf{y}}(\omega_i^{2^j}) \leq c^{-2^j} \gamma(2^j)!$  and  $L_{\mathbf{u}}(\omega_i^{2^j}) \leq c^{-2^j} \gamma(2^j)!$  for all  $j = 1, \dots, d$  and all  $i = 1, \dots, n$ . As  $\mathbf{A}$  is compact and  $q_1(\mathbf{a}) = M - \|\mathbf{a}\|^2$ , it follows that  $L_{\mathbf{y}}(a_i^{2^j}) \leq M^j$ ,  $j = 1, \dots, d$ ,  $i = 1, \dots, L$ . By the same argument using now  $g_1(\mathbf{x}) = M - \|\mathbf{x}\|^2$ ,  $L_{\mathbf{y}}(x_i^{2^j}) \leq M^j$ ,  $L_{\mathbf{u}}(x_i^{2^j}) \leq M^j$ , and  $L_{\mathbf{v}}(x_i^{2^j}) \leq M^j$ ,  $j = 1, \dots, d$ ,  $i = 1, \dots, L$ .

Next, as  $y_{00} \leq 1$ ,  $\mathbf{u}_{00} \leq 1$  and  $v_{00} = 1$ , and  $\mathbf{M}_d(\mathbf{y}), \mathbf{M}_d(\mathbf{u}), \mathbf{M}_d(\mathbf{v}) \succeq 0$ , by invoking [26, ], we obtain

$$|y_{\alpha\beta}| \leq \max[1, \max_i [L_{\mathbf{y}}(x_i^{2d}), L_{\mathbf{y}}(\omega_i^{2d})]] = \tau_1,$$

$$|u_{\alpha\beta}| \leq \max[1, \max_i [L_{\mathbf{y}}(x_i^{2d}), L_{\mathbf{u}}(\omega_i^{2d})]] = \tau_2; \quad |v_{\alpha\beta}| \leq \max[1, M^d] = \tau_3,$$

for all  $(\alpha, \beta)$ . This implies that the feasible set of (4.5) is compact and so (4.5) has an optimal solution  $(\mathbf{y}^d, \mathbf{u}^d, \mathbf{v}^d)$  for every  $d \geq d_0$ .

For every  $d$  let  $\tau_d := \max[\tau_1, \tau_2, \tau_3]$ . Next, by completing with zeros, consider the finite vectors  $\mathbf{y}^d$ ,  $\mathbf{u}^d$  and  $\mathbf{v}^d$  has infinite sequences. As  $|y_{\alpha\beta}| \leq \tau_d$ ,  $|u_{\alpha\beta}| \leq \tau_d$  and  $|v_{\alpha\eta}| \leq \tau_d$ , whenever  $|\alpha + \beta| \leq 2d$  and  $|\alpha + \eta| \leq 2d$ , by a standard argument <sup>4</sup> there exists a subsequence  $(d_k)_{k \in \mathbb{N}}$  and infinite sequences  $\mathbf{y}^* = (y_{\alpha\beta}^*)$ ,  $\mathbf{u}^* = (u_{\alpha\beta}^*)$ , and  $\mathbf{v}^* = (v_{\alpha\eta})$ ,  $\alpha \in \mathbb{N}^n$ ,  $\beta \in \mathbb{N}^p$ , and  $\eta \in \mathbb{N}^L$ , such that

$$(7.4) \quad \lim_{k \rightarrow \infty} y_{\alpha\beta}^{d_k} = y_{\alpha\beta}^*, \quad \lim_{k \rightarrow \infty} u_{\alpha\beta}^{d_k} = u_{\alpha\beta}^*, \quad \alpha \in \mathbb{N}^n, \beta \in \mathbb{N}^p,$$

$$(7.5) \quad \lim_{k \rightarrow \infty} v_{\alpha\eta}^{d_k} = v_{\alpha\eta}^*, \quad \alpha \in \mathbb{N}^n, \eta \in \mathbb{N}^L.$$

Next, fix  $r \in \mathbb{N}$  arbitrary. By (7.4) and (7.5),  $\mathbf{M}_r(\mathbf{y}^*) \succeq 0$ ,  $\mathbf{M}_r(\mathbf{u}^*) \succeq 0$  and  $\mathbf{M}_r(\mathbf{v}^*) \succeq 0$ . In addition:

$$L_{\mathbf{y}^*}(\omega_i^{2j})^{-1/2j} \geq c\gamma^{-1/2j} (2j!)^{-1/2j}, \quad \forall i, j,$$

and similarly

$$L_{\mathbf{u}^*}(\omega_i^{2j})^{-1/2j} \geq c\gamma^{-1/2j} (2j!)^{-1/2j}, \quad \forall i, j.$$

Also

$$L_{\mathbf{y}^*}(x_i^{2j})^{-1/2j}, L_{\mathbf{u}^*}(x_i^{2j})^{-1/2j}, L_{\mathbf{v}^*}(x_i^{2j})^{-1/2j} \geq M^{-1/2} \quad \forall i, j.$$

Therefore as  $\sum_{j=1}^{\infty} (2j!)^{-1/2j} = +\infty$ , one obtains

$$(7.6) \quad \sum_{j=1}^{\infty} L_{\mathbf{y}^*}(\omega_i^{2j})^{-1/2j} = +\infty, \quad \text{and} \quad \sum_{j=1}^{\infty} L_{\mathbf{y}^*}(x_i^{2j})^{-1/2j} = +\infty, \quad \forall i, j,$$

and similarly for  $\mathbf{u}^*$ ,  $\mathbf{v}^*$ . In summary, the three sequences  $\mathbf{y}^*$ ,  $\mathbf{u}^*$  and  $\mathbf{v}^*$  satisfy the multivariate Carleman's condition (2.1). As  $\mathbf{M}_d(\mathbf{y}^*)$ ,  $\mathbf{M}_d(\mathbf{u}^*)$ ,  $\mathbf{M}_d(\mathbf{v}^*) \succeq 0$ , they have a representing measure  $\phi^*$ ,  $\varphi^*$  and  $\psi^*$  respectively on  $\mathbb{R}^n \times \mathbb{R}^p$ ,  $\mathbb{R}^n \times \mathbb{R}^p$  and  $\mathbb{R}^n \times \mathbb{R}^L$ .

Next, as (4.4) holds, the quadratic module of  $\mathbb{R}[\mathbf{x}, \mathbf{a}]$  generated by the polynomials  $(g_j, q_\ell)$  is Archimedean. Therefore, as  $\mathbf{M}_d(g_j \mathbf{v}^*) \succeq 0$  and  $\mathbf{M}_d(q_\ell \mathbf{v}^*) \succeq 0$  for all  $d$  and all  $j = 1, \dots, m$ ,  $\ell = 1, \dots, L$ , by Putinar's Theorem [33], the measure  $\psi^*$  is supported on  $\mathbf{X} \times \mathbf{A}$ . Also, as (4.4) holds, the quadratic module of  $\mathbb{R}[\mathbf{x}]$  generated by the polynomials  $(g_j)$  is Archimedean. Hence the marginal  $\phi_{\mathbf{x}}^*$  of  $\phi$  is supported on  $\mathbf{X}$ . If  $\Omega$  is compact (and as then  $s_1(\omega) = M - \|\omega\|^2$ ) a similar argument shows that  $\phi^*$  is supported on  $\mathbf{K}$ .

If  $\Omega$  is not compact, then by (7.3) and (7.4) we have  $L_{\mathbf{y}^*}(\omega_i^{2j}) \leq c^{-2j} \gamma (2j!)$  for all  $i, j$ . As  $\mathbf{M}_d(s_\ell \mathbf{y}^*) \succeq 0$  for all  $\ell$ , and  $\mathbf{M}_d(-f \mathbf{y}^*) \succeq 0$  for all  $d$ , then by [21,

<sup>4</sup>Let  $(u^n)_{n \in \mathbb{N}}$  be a sequence of infinite sequences such that  $\sup_n |u_i^n| < \tau_i$  for all  $i = 1, \dots$ , and let  $\hat{u}_i^n := u_i^n / \tau_i$ , for all  $i, n$ . Then  $(\hat{u}^n) \subset \mathbf{B}_1$  where  $\mathbf{B}_1$  is the unit ball of  $\ell_\infty$ . By weak-star sequential compactness of  $\mathbf{B}_1$ , there is a subsequence  $(n_k)$  and  $\hat{u} \in \mathbf{B}_1$  such that  $\hat{u}^{n_k} \rightarrow \hat{u}$  for the  $\sigma(\ell_\infty, \ell_1)$  weak-star topology of  $\ell_\infty$ . In particular,  $\hat{u}_i^{n_k} \rightarrow \hat{u}_i$ , as  $k \rightarrow \infty$ , for all  $i = 1, \dots$ , which implies  $u_i^{n_k} \rightarrow \tau_i \hat{u}_i$ , as  $k \rightarrow \infty$ , for all  $i = 1, \dots$

Theorem 2.2, p. 2494]<sup>5</sup>,  $f(\mathbf{x}, \omega) \leq 0$  and  $s_\ell(\omega) \geq 0$ ,  $\ell = 1, \dots, \bar{s}$ , on the support of  $\phi^*$ . That is,  $\text{support}(\phi^*) \subset \mathbf{K}$ .

Hence  $(\phi^*, \psi^*)$  is a feasible solution of (3.5). But as  $\phi^*(\mathbf{K}) = \lim_{d \rightarrow \infty} \rho_d \geq \rho$ , we conclude that  $(\phi^*, \psi^*)$  is an optimal solution with value  $\rho$ .  $\square$

### 7.5. Verifying Assumption 2.3 and Assumption 2.3.

7.5.1.  *$\mathbf{A}$  is a finite set.* In this case  $\Omega = \mathbb{R}^p$  and  $\mathbf{A} = \{1, \dots, \kappa\}$ . Then Assumption 2.2 holds and Assumption 2.3 holds whenever it holds for each individual  $\mu_i$ ,  $i = 1, \dots, \kappa$ . The set  $\mathcal{M}_{\mathbf{a}}$  can be identified with the simplex  $\Delta = \{\lambda \in \mathbb{R}^\kappa : \sum_i \lambda = 1, \lambda \geq 0\}$ . In Theorem 3.2, the conditional probability  $\hat{\phi}^*(d\mathbf{a}|\mathbf{x})$ ,  $\mathbf{x} \in \mathbf{S}$ , of the optimal solution  $\phi^*$ , identifies the worst-case distribution  $\mu_{\mathbf{a}(\mathbf{x})} \in \mathbf{A}$  for every  $\mathbf{x} \in \mathbf{S}$ .

7.5.2. *Mixture of Multivariate Gaussian distributions.* In the general case  $\Omega = \mathbb{R}^p$ ,  $\mathbf{a} = (\theta, \Sigma)$  with  $\underline{\theta} \leq \theta \leq \bar{\theta}$ , where  $\underline{\theta}, \bar{\theta} \in \mathbb{R}^p$ , and  $\Sigma = \Sigma^T = (\sigma_{ij}) \in \mathbb{R}^{p \times p}$ , with  $\underline{\delta} \mathbf{I} \preceq \Sigma \preceq \bar{\delta} \mathbf{I}$  and  $\underline{\delta} > 0$ . That is,

$$d\mu_{\mathbf{a}}(\omega) = \frac{1}{\sqrt{(2\pi)^p \det(\Sigma)}} \exp\left(-\frac{1}{2}(\omega - \theta)\Sigma^{-1}(\omega - \theta)\right) d\omega,$$

The measurability condition in Assumption 2.2(i) follows from Fubini-Tonelli's theorem. Assumption 2.2(ii) is also satisfied. For instance, the fourth-order central moments read (see e.g. [https://en.wikipedia.org/wiki/Multivariate\\_normal\\_distribution#Higher\\_moments](https://en.wikipedia.org/wiki/Multivariate_normal_distribution#Higher_moments)):

$$\int (\omega_i - \theta_i)^4 d\mu_{\mathbf{a}}(\omega) = 3\sigma_{ii}^2; \quad \int (\omega_i - \theta_i)^3 (\omega_j - \theta_j) d\mu_{\mathbf{a}}(\omega) = 3\sigma_{ii}\sigma_{ij}$$

$$\int (\omega_i - \theta_i)^2 (\omega_j - \theta_j)^2 d\mu_{\mathbf{a}}(\omega) = \sigma_{ii}\sigma_{jj} + 2\sigma_{ij}^2,$$

$$\int (\omega_i - \theta_i)^2 (\omega_j - \theta_j) (\omega_k - \theta_k) d\mu_{\mathbf{a}}(\omega) = \sigma_{ii}\sigma_{jk} + 2\sigma_{ij}\sigma_{ik},$$

$$\int (\omega_i - \theta_i) (\omega_j - \theta_j) (\omega_k - \theta_k) (\omega_\ell - \theta_\ell) d\mu_{\mathbf{a}}(\omega) = \sigma_{ij}\sigma_{k\ell} + \sigma_{ik}\sigma_{j\ell} + \sigma_{i\ell}\sigma_{jk},$$

and higher-order central moments are homogeneous polynomials in the entries of  $\Sigma$ . This immediately implies that non-central moments are polynomials in  $(\sigma_{ij})$  and  $\theta$ . Assumption 2.2(iii) is also straightforward as  $\mu_{\mathbf{a}}$  has a density w.r.t.  $d\omega$ , everywhere positive. Concerning Assumption 2.2(iv), let  $h$  be bounded continuous on  $\mathbf{X} \times \Omega$ . With the change of variable  $\mathbf{u} = \Sigma^{-1/2}(\omega - \theta)$  one has

$$H(\mathbf{x}, \mathbf{a}) := \int_{\Omega} h(\mathbf{x}, \omega) d\mu_{\mathbf{a}}(\omega) = \frac{1}{\sqrt{(2\pi)^p}} \int_{\Omega} h(\mathbf{x}, \Sigma^{1/2} \mathbf{u} + \theta) \exp\left(-\frac{1}{2}\|\mathbf{u}\|^2\right) d\mathbf{u},$$

and since  $h$  is bounded and continuous, it follows that  $H$  is continuous in  $(\mathbf{x}, \mathbf{a}) \in \mathbf{X} \times \mathbf{A}$ . Finally, Assumption 2.3 also holds.

<sup>5</sup>In the proof of Theorem 2.2 in [21],  $c = 1$ , but the proof can be extended easily to arbitrary  $c > 0$

7.5.3. *Mixture of exponential distributions.* In this case  $\Omega = \mathbb{R}_+^p$ ,  $\mathbf{a} = (a_1, \dots, a_p)$  with  $\mathbf{a} \in \mathbf{A} := [\underline{\mathbf{a}}, \bar{\mathbf{a}}]$ ,  $\underline{\mathbf{a}} > 0$ , and

$$d\mu_{\mathbf{a}}(\omega) = \left( \prod_{i=1}^p \frac{1}{a_i} \right) \exp\left(-\sum_{i=1}^p \frac{\omega_i}{a_i}\right) d\omega = \otimes_{i=1}^p d\mu_{a_i}(\omega_i)$$

with  $d\mu_{a_i}(\omega_i) = \frac{1}{a_i} \exp(-\omega_i/a_i) d\omega_i$ ,  $i = 1, \dots, p$ .

Again, the measurability condition in Assumption 2.2(i) follows from Fubini-Tonelli's theorem. Then for Assumption 2.2(ii),

$$\int_{\Omega} \omega^\beta d\mu_{\mathbf{a}}(\omega) = \prod_{i=1}^p \left( \frac{1}{a_i} \int_{\mathbb{R}_+} \omega_i^{\beta_i} \exp(\omega_i/a_i) d\omega_i \right) = \mathbf{a}^\beta \prod_{i=1}^p \beta_i! \in \mathbb{R}[\mathbf{a}],$$

and Assumption 2.2(iii) also holds. Like for the Gaussian, and after the change of variable  $u_i = \omega_i/a_i$ ,  $i = 1, \dots, p$ , one shows easily that Assumption 2.2(iv) holds. Finally for Assumption 2.3,

$$\int_{\Omega} \exp(c|\omega|) d\mu_{\mathbf{a}}(\omega) = \left( \prod_{i=1}^p \frac{1}{a_i} \right) \exp\left(-\sum_{i=1}^p \omega_i \left(\frac{1}{a_i} - c\right)\right) d\omega < \infty,$$

whenever  $c < 1/a_i$  for all  $i = 1, \dots, p$ .

7.5.4. *Mixture of elliptical's.* Assumption 2.2(ii) holds for Example 1.3. For instance with  $\theta : \mathbb{R}_+ \rightarrow \mathbb{R}_+$  such that  $\int_{\mathbb{R}} t^k \theta(t^2) dt < \infty$  for all  $k$ , and  $s = \int_{\mathbb{R}} \theta(t^2) dt$ , let

$$d\mu_{\mathbf{a}}(\omega) = \frac{1}{s\sigma} \theta((\omega - a)^2/\sigma^2) d\omega, \quad \mathbf{a} = (a, \sigma) \in \mathbf{A}.$$

Then

$$\int \omega^j d\mu_{\mathbf{a}}(\omega) = \frac{1}{s} \int_{\mathbb{R}} (\sigma t + a)^j \theta(t^2) dt = p_j(a, \sigma), \quad j = 0, 1, \dots,$$

7.5.5. *Mixture of Poisson's.* Assumption 2.2(ii) holds for Example 1.4. For instance

$$p_1(\mathbf{a}) = \int_{\Omega} \omega d\mu_{\mathbf{a}}(\omega) = a; \quad p_2(\mathbf{a}) = \int_{\Omega} \omega^2 d\mu_{\mathbf{a}}(\omega) = a^2 + a.$$

7.5.6. *Mixture of Binomial's.* Assumption 2.2(ii) holds for Example 1.5. For instance

$$p_1(\mathbf{a}) = \int_{\Omega} \omega d\mu_{\mathbf{a}}(\omega) = Na; \quad p_2(\mathbf{a}) = \int_{\Omega} \omega^2 d\mu_{\mathbf{a}}(\omega) = Na(1-a).$$

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