

**Concentration Inequalities and Applications**

**Content.**

**1 Talagrand's inequality**

Let  $(\Omega_i, \mathcal{F}_i, \mu_i)$  be probability spaces ( $i = 1, \dots, n$ ). Let  $\mu = \mu_1 \otimes \dots \otimes \mu_n$  be product measure on  $X = \Omega_1 \times \dots \times \Omega_n$ . Let  $x = (x_1, \dots, x_n) \in X$  be a point in this product space.

Hamming distance over  $X$ :

$$d(x, y) = |\{i \leq n : x_i \neq y_i\}| = \sum_{i=1}^n \mathbf{1}_{\{x_i \neq y_i\}}$$

$\alpha$ -weighted Hamming distance over  $X$  for  $a \in \mathbb{R}_+^n$ :

$$d_a(x, y) = \sum_{i=1}^n a_i \mathbf{1}_{\{x_i \neq y_i\}}$$

Also  $|a| = \sqrt{\sum a_i^2}$ .

Control-distance from a set: for set  $A \subseteq X$ , and  $x \in X$ :

$$\mathcal{D}_A^c(x) = \sup_{|a|=1} d_a(x, A) = \inf\{d_a(x, y) : y \in A\}$$

**Theorem 1** (Talagrand). *For every measurable non-empty set  $A$  and product-measure  $\mu$ ,*

$$\int \exp\left(\frac{1}{4}(\mathcal{D}_A^c)^2\right) d\mu \leq \frac{1}{\mu(A)}$$

In particular,

$$\mu(\{\mathcal{D}_A^c \geq t\}) \leq \frac{1}{\mu(A)} \exp\left(-\frac{t^2}{4}\right)$$

## 2 Application of Talagrand's Inequality

### 2.1 Concentration of Lipschitz functions.

Let  $F : X \rightarrow \mathbb{R}$  for product space  $X = \Omega_1 \times \dots \times \Omega_n$  such that for every  $x \in X$ , there exists  $a \equiv a(x) \in \mathbb{R}_+^n$  with  $|a| = 1$  so that for each  $y \in Y$ ,

$$F(x) \leq F(y) + d_a(x, y) \quad (1)$$

Why does every 1-Lipschitz function is essentially like (1)?

Consider a 1-Lipschitz function  $f : X \rightarrow \mathbb{R}$  such that

$$|f(x) - f(y)| \leq \sum_i |x_i - y_i| \text{ (defined on } \Omega_i \text{) for all } x, y \in X.$$

Let  $d_i = \max_{x, y \in \Omega} |x_i - y_i|$ . We assume  $d_i$  is bounded for all  $i$ . Then,

$$|f(x) - f(y)| \leq \sum_i |x_i - y_i| \leq \sum_i \mathbf{1}_{\{x_i \neq y_i\}} d_i$$

Therefore,

$$\frac{f(x) - f(y)}{\sqrt{\sum_i d_i^2}} \leq \sum_i \frac{d_i}{\sqrt{\sum_i d_i^2}} \mathbf{1}_{\{x_i \neq y_i\}} = d_a(x, y) \text{ with } a_i = \frac{d_i}{\sqrt{\sum_i d_i^2}}$$

Thus  $F(x) = \frac{f(x)}{\|d\|_2}$  where  $\|d\|_2 = \sqrt{\sum_i d_i^2}$ .

Let  $A = \{F \leq m\}$ . By definition of  $\mathcal{D}_A^c(x)$ ,

$$\mathcal{D}_A^c(x) = \sup_{a:|a|=1} d_a(x, A) \geq d_a(x, y)$$

for a given  $a$  such that  $|a| = 1$  and  $y \in A$ . Now for any  $y \in A$ , by definition  $F(y) \leq m$ . Then,

$$F(x) \leq F(y) + d_a(x, y) \leq m + \mathcal{D}_A^c(x)$$

which implies  $\{F \geq m + r\} \subseteq \{\mathcal{D}_A^c(x) \geq r\}$ . By Talagrand's inequality, for any  $r \geq 0$ ,

$$\mathbb{P}(\{f \geq m + r\}) \leq \mathbb{P}(\{\mathcal{D}_A^c \geq r\}) \leq \frac{1}{\mathbb{P}(A)} \exp\left(-\frac{r^2}{4}\right)$$

That is,

$$\mathbb{P}(\{F \leq m\})\mathbb{P}(\{F \geq m + r\}) \leq \exp\left(-\frac{r^2}{4}\right) \quad (2)$$

The median of  $F$ ,  $m_F$  is precisely such that

$$\mathbb{P}(F \leq m_F) \geq \frac{1}{2}, \mathbb{P}(F \geq m_F) \geq \frac{1}{2}$$

Choose  $m = m_F$ ,  $m = m_F - r$  in (2) to obtain:

$$\mathbb{P}(F \geq m_F + r) \leq 2 \exp(-\frac{r^2}{4}), \mathbb{P}(F \leq m_F - r) \leq 2 \exp(-\frac{r^2}{4}) \quad (3)$$

Thus,

$$\mathbb{P}(|F - m_F| \geq r) \leq 4 \exp(-\frac{r^2}{4})$$

## 2.2 Further Application for Linear Functions

Consider the independent random variables  $Y_1, \dots, Y_n$  on some probability space  $(\Omega, \mathcal{F}, \mathbb{P})$ . Let the constants  $(u_i, v_i)$ ,  $1 \leq i \leq n$  such that

$$u_i \leq Y_i \leq v_i$$

Set  $Z = \sup_{t \in T} \langle t, Y \rangle \equiv \sum_{i=1}^n t_i Y_i$  where  $T$  is some finite, countable or compact set of vectors in  $\mathbb{R}_+$ . We would be interested in situations where

$$\sigma^2 = \sup_{t \in T} \sum_i t_i^2 (v_i - u_i)^2 \leq \infty$$

We wish to apply (3) to this setting by choosing

$$F(x) = \sup_{t \in T} \langle t, x \rangle$$

where  $x \in X$  and  $X = \prod_{i=1}^n [u_i, v_i]$ . Given that  $T$  is compact,  $F(x) = \langle t^*(x), x \rangle$  for some  $t = t^*(x) \in T$ , given  $x$ .

$$\begin{aligned} F(x) &= \sum_{i=1}^n t_i x_i \leq \sum_i t_i y_i + \sum_i |t_i| |y_i - x_i| \\ &\leq \sum_i t_i y_i + \sum_i |t_i| (v_i - u_i) \mathbf{1}_{(y_i \neq x_i)} \quad (\text{let } d_i = |t_i| (v_i - u_i)). \\ &\leq \sup_{\tilde{t} \in T} \langle \tilde{t}, y \rangle + \left( \sum_i \frac{d_i}{\|d\|_2} \mathbf{1}_{(y_i \neq x_i)} \right) \|d\|_2 \\ &= F(y) + d_a(x, y) \|d\|_2 \quad (\text{where let } \sigma = \|d\|_2 = \sqrt{\sup_{t \in T} \sum_i t_i^2 (v_i - u_i)^2}) \\ &= F(y) + \sigma d_a(x, y) \end{aligned} \quad (4)$$

By selection of  $f \equiv \frac{1}{\sigma}F$ , (3) can be applied to  $f$ :

$$\mathbb{P}(|f - m_f| \geq r) \leq 4 \exp\left(-\frac{r^2}{4}\right)$$

Let  $r = \frac{\gamma}{\sigma}$ , then  $\mathbb{P}(|\sigma f - \sigma m_f| \geq \gamma) \leq 4 \exp\left(-\frac{\gamma^2}{4\sigma^2}\right)$ . That is,

$$\mathbb{P}(|F - m_F| \geq \gamma) \leq 4 \exp\left(-\frac{\gamma^2}{4\sigma^2}\right)$$

Now,

$$\begin{aligned} \mathbb{E}[F] &= \int_0^\infty \mathbb{P}(F \geq s) ds \text{ (assume } t \equiv 0 \in T) \\ &\leq \int_0^{m_F} 1 ds + \int_0^\infty \mathbb{P}(F \geq m_F + \gamma) d\gamma \\ &\leq m_F + \int_0^\infty 2 \exp\left(-\frac{\gamma^2}{4\sigma^2}\right) d\gamma \\ &\leq m_F + \int_0^\infty 2 \exp\left(-\frac{\gamma^2}{4\sigma^2}\right) d\gamma \\ &= m_F + 2\sqrt{8\pi\sigma^2} \int_0^\infty \frac{1}{\sqrt{2\pi}4\sigma^2} \exp\left(-\frac{\gamma^2}{4\sigma^2}\right) d\gamma \\ &= m_F + 2\sqrt{2\pi}\sigma \end{aligned}$$

Thus,

$$|\mathbb{E}[F] - m_F| \leq 2\sqrt{2\pi}\sigma$$

### 2.3 More Intricate Application

Longest increasing subsequence:

Let  $X_1, \dots, X_n$  be points in  $[0, 1]$  chosen independently as a product measure. Let  $L_n(X_1, \dots, X_n)$  be the length of longest increasing subsequence. (Note that  $L_n(\cdot)$  is not obviously Lipschitz). Talagrand's inequality implies its concentration.

**Lemma 1.** *Let  $m_n$  be median of  $L_n$ . Then for any  $r > 0$ , we have*

$$\mathbb{P}(L_n \geq m_n + r) \leq 2 \exp\left(-\frac{r^2}{4(m_n + r)}\right)$$

$$\mathbb{P}(L_n \leq m_n - r) \leq 2 \exp\left(-\frac{r^2}{4m_n}\right)$$

*Proof.* Let us start by establishing first inequality. Select  $A = \{L_n \leq m_n\}$ . Clearly, by definition  $\mathbb{P}(A) \geq \frac{1}{2}$ . For a  $x$  such that  $L_n(x) > m_n$ , (i.e.  $x \in A$ ), consider any  $y \in A$ . Now, let set  $I \subseteq [n]$  be indices that give rise to longest increasing subsequence in  $x$ : i.e. say  $I = \{i_1, \dots, i_p\}$  then  $x_{i_1} < x_{i_2} < \dots < x_{i_p}$  and  $p$  is the maximum length of any such increasing subsequence of  $x$ . Let  $J = \{i \in I : x_i \neq y_i\}$  for given  $y$ . Since  $I \setminus J$  is an index set that corresponds to a increasing subsequence of  $y$  (since for  $i \in I \setminus J$ ;  $x_i = y_i$  and  $I$  is index set of increasing subsequence of  $I$ ); we have that (using fact that  $L_n(y) \leq m_n$  as  $y \in A$ )

$$|I \setminus J| \leq m_n$$

That is,

$$\begin{aligned} L_n(x) = |I| &\leq |I \setminus J| + |J| \\ &\leq L_n(y) + \sum_{i \in I} \mathbf{1}(x_i \neq y_i) \\ &\leq L_n(y) + \sqrt{L_n(x)} \left[ \sum_{i=1}^n \frac{1}{\sqrt{L_n(x)}} \mathbf{1}(i \in I) \mathbf{1}(x_i \neq y_i) \right] \end{aligned}$$

Define

$$a_i(x) = \begin{cases} \frac{1}{\sqrt{L_n(x)}}, & \text{if } i \in I \\ 0, & \text{o.w.} \end{cases}$$

Then  $|a| = 1$  since  $|I| = L_n(x)$  by definition, and hence,

$$L_n(x) \leq L_n(y) + \sqrt{L_n(x)} d_a(x, y) \leq m_n + \sqrt{L_n(x)} \mathcal{D}_A^c(x)$$

Equivalently,

$$\mathcal{D}_A^c(x) \geq \frac{L_n(x) - m_n}{\sqrt{L_n(x)}}$$

For  $x$  such that  $L_n(x) \geq m_n + r$ , the RHS of above is minimal when  $L_n(x) = m_n + r$ . Therefore, we have

$$\mathcal{D}_A^c(x) \geq \frac{L_n(x) - m_n}{\sqrt{L_n(x)}}$$

For  $x$  such that  $L_n(x) \geq m_n + r$ , the RHS of above is minimal when  $L_n(x) = m_n + r$ . Therefore, we have

$$\mathcal{D}_A^c(x) \geq \frac{r}{\sqrt{m_n + r}}$$

That is

$$L_n(x) \geq m_n + r \Rightarrow \mathcal{D}_A^c(x) \geq \frac{r}{\sqrt{m_n + r}} \text{ for } A = \{L_n \leq m_n\}$$

Putting these together, we have

$$\mathbb{P}(L_n \geq m_n + r) \leq \mathbb{P}(\mathcal{D}_A^c \geq \frac{r}{\sqrt{m_n + r}}) \leq \frac{1}{2P(A)} \exp(-\frac{r^2}{4(m_n + r)})$$

But  $\mathbb{P}(A) = \mathbb{P}(L_n \leq m_n) \geq \frac{1}{2}$ , we have that

$$\mathbb{P}(L_n \geq m_n + r) \leq 2 \exp(-\frac{r^2}{4(m_n + r)})$$

To establish lower bound, replace argument of the above with  $x$  such that  $L_n(x) \geq s + u$ ,  $A = \{L_n \leq s\}$ . Then we obtain,

$$\mathcal{D}_A^c(x) \geq \frac{u}{\sqrt{s + u}}$$

Select  $s = m_n - r$ ,  $u = r$ . Then whenever  $x$  is such that  $L_n(x) \geq s + u = m_n$  and for  $A = \{L_n \leq s\} = \{L_n \leq m_n - r\}$ .

$$\mathcal{D}_A^c(x) \geq \frac{r}{\sqrt{m_n}}$$

Thus,

$$\mathbb{P}(L_n \geq m_n) \leq \mathbb{P}(\mathcal{D}_A^c \geq \frac{r}{\sqrt{m_n}}) \leq \frac{1}{\mathbb{P}(L_n \leq m_n - r)} \exp(-\frac{r^2}{4m_n})$$

which implies

$$\mathbb{P}(L_n \leq m_n - r) \leq 2 \exp(-\frac{r^2}{4m_n})$$

This completes the proof.  $\square$

### 3 Proof of Talagrand's Inequality

Preparation. Given set  $A$ ,  $x \in X$ :  $\mathcal{D}_A^c(x) = \sup_{a \in \mathcal{R}_+^n} (d_a(x, A) - \inf_{y \in A} d_a(x, y))$ . Let

$$U_A(x) = \{s \in \{0, 1\}^n : \exists y \in A \text{ with } s \triangleq \mathbf{1}(x \neq y)\} = \{\mathbf{1}(x \neq y) : y \in A\}$$

and let

$$V_A(x) = \text{Convex-hull}(U_A(x)) = \left\{ \sum_{s \in U_A(x)} \alpha_s S : \sum \alpha_s = 1, \alpha_s \geq 0 \text{ for all } s \in U_A(x) \right\}$$

Thus,

$$x \in A \Leftrightarrow \mathbf{1}(x \neq x) = 0 \in U_A(x) \Leftrightarrow 0 \in V_A(x)$$

It can therefore be checked that

**Lemma 2.**

$$\mathcal{D}_A^c(x) = d(0, V_A(x)) \equiv \inf_{y \in V_A(x)} |y|$$

*Proof.* (i)  $\mathcal{D}_A^c(x) \leq \inf_{y \in V_A(x)} |y|$ : since  $\inf_{y \in V_A(x)} |y|$  is achieved, let  $Z$  be such that  $|Z| = \inf_{y \in V_A(x)} |y|$ . Now for any  $a \in \mathbb{R}_+^n$ ,  $|a| = 1$ :

$$\inf_{y \in V_A(x)} a \cdot y \leq a \cdot z \leq |a||z| = |z|$$

Since  $\inf_{y \in V_A(x)} a \cdot y$  is linear programming, the minimum is achieved at an extreme point. That is, there exists  $s \in U_A(x)$  such that

$$\inf_{y \in V_A(x)} a \cdot y = \inf_{s \in U_A(x)} a \cdot s = \inf_{y \in A} d_a(x, y) \text{ for some } y \in A.$$

Since this is true for all  $a$ , it follows that,

$$\sup_{|a|=1, a \in \mathbb{R}_+^n} \inf_{y \in A} d_a(x, y) \leq |z| \equiv \inf_{y \in V_A(x)} |y|$$

(ii)  $\mathcal{D}_A^c(x) \geq \inf_{y \in V_A(x)} |y|$ : Let  $z$  be the one achieving minimum in  $V_A(x)$ . Then due to convexity of the objective (equivalently  $|y|^2 = \sum y_i^2 = f(y)$ ) and of the domain, we have for any  $y \in V_A(x)$ ,  $\nabla f(z)(y - z) \geq 0$  for any  $y \in V_A(x)$ .  $\nabla f(z) = \nabla(z \cdot z) = 2z$ . Therefore the condition implies

$$(y - z)z \geq 0 \Leftrightarrow y \cdot z \geq z \cdot z = |z|^2 \Rightarrow y \cdot \frac{z}{|z|} \geq |z|$$

Thus, for  $a = \frac{z}{|z|} \in \mathbb{R}_+^n$ ,  $|a| = 1$ , we have that

$$\inf_{y \in V_A(x)} a \cdot y \geq |z|$$

But for any given  $a$ ,  $\inf_{y \in V_A(x)} a \cdot y = \inf_{s \in U_A(x)} a \cdot s = d_a(x, A)$  as explained before. That is,  $\sup_{a: |a|=1} d_a(x, A) \geq |z| = \inf_{y \in V_A(x)} |y|$ . This completes the proof.  $\square$

Now we are ready to establish the inequality of Talagrand. The proof is via induction. Consider  $n = 1$ , given set  $A$ . Now,

$$\mathcal{D}_A^c(x) = \sup_{a \in \mathbb{R}_+^n, |a|=1} \inf_{y \in A} d_a(x, y) = \inf_{y \in A} \mathbf{1}(x \neq y) = \begin{cases} 0, & \text{for } x \in A \\ 1, & \text{for } x \notin A \end{cases}$$

Then,

$$\begin{aligned} \int \exp(D^2/4) dP &= \int_A \exp(0) dP + \int_{A^c} \exp(1/4) dP \\ &= P(A) + e^{1/4}(1 - P(A)) \\ &= e^{1/4} - (e^{1/4} - 1)P(A) \leq \frac{1}{P(A)} \end{aligned} \quad (5)$$

Let  $f(x) = e^{1/4} - (e^{1/4} - 1)x$  and  $g(x) = \frac{1}{x}$ . Because  $f(x)$  is a decreasing function of  $x$ ,  $g(x)$  is a decreasing convex function. Thus, the result is established for  $n = 1$ .

Induction hypothesis. Let it hold for some  $n$ . We shall assume for ease of the proof that  $\Omega_1 = \Omega_2 = \dots = \Omega_n = \dots = \Omega$ . L

Let  $A \subset \Omega^{n+1}$ . Let  $B$  be its projection on  $\Omega^n$ . Let  $A(\omega)$ ,  $\omega \in \Omega$  be section of  $A$  along  $\omega$ : if  $x \in \Omega^n$ ,  $\omega \in \Omega$  then  $z = (x, \omega) \in \Omega^{n+1}$ . We observe the following:

if  $s \in U_{A(\omega)}(x)$ , then  $(s, 0) \in U_A(z)$ . Because, for some  $y \in \Omega^n$  such that  $(y, \omega) \in A$ ,  $s = \mathbf{1}(x \neq y)$ . Therefore,  $(s, 0) = (\mathbf{1}(x \neq y), \mathbf{1}(\omega \neq \omega)) = \mathbf{1}(z \neq (y, \omega))$  where  $(y, \omega) \in A$ . Further, if  $t \in U_B(x)$ , then  $(t, 1) \in U_A(z)$ . This is because of the following:  $B = \{\tilde{x} \in \Omega^n : (\tilde{x}, \tilde{\omega}) \in A \text{ for some } \tilde{\omega} \in \Omega\}$ . Now if  $t \in U_B(x)$ , then  $\exists y \in B$  such that  $t = \mathbf{1}(x \neq y)$ . Now  $(t, 1) = (\mathbf{1}(x \neq y), \mathbf{1}(\tilde{\omega} \neq \omega)) = \mathbf{1}(z \neq (y, \tilde{\omega}))$  as long as there exists  $\tilde{\omega}$  so that  $(y, \tilde{\omega}) \in A$  and  $\tilde{\omega} \neq \omega$ .

Given this, it follows that if  $\xi \in V_{A(\omega)}(x)$ ,  $\zeta \in V_B(x)$ , and  $\theta \in [0, 1]$ , then  $((\theta\xi + (1 - \theta)\zeta), 1 - \theta) \in V_A(z)$ . Recall that

$$\begin{aligned} \mathcal{D}_A^c(z)^2 &= \inf_{y \in V_A(z)} |y|^2 \leq (1 - \theta)^2 + |\theta\xi + (1 - \theta)\zeta|^2 \\ &\leq (1 - \theta)^2 + \theta|\xi|^2 + (1 - \theta)|\zeta|^2 \end{aligned} \quad (6)$$

Therefore,

$$\begin{aligned} \mathcal{D}_A^c(z)^2 &\leq (1 - \theta)^2 + \theta \inf_{\xi \in V_{A(\omega)}(x)} |\xi|^2 + (1 - \theta) \inf_{\zeta \in V_B(x)} |\zeta|^2 \\ &= (1 - \theta)^2 + \theta \mathcal{D}_{A(\omega)}^c(x)^2 + (1 - \theta) \mathcal{D}_B^c(x)^2 \end{aligned}$$

By Hölder's inequality, and the induction hypothesis, for  $\forall \omega \in \Omega$ ,

$$\begin{aligned}
& \int_{\Omega^n} e^{\mathcal{D}_A^c(x,\omega)^2/4} dP(x) \\
& \leq \int_{\Omega^n} \exp\left(\frac{(1-\theta)^2 + \theta \mathcal{D}_{A(\omega)}^c(x)^2 + (1-\theta) \mathcal{D}_B^c(x)^2}{4}\right) dP(x) \\
& \leq \exp\left(\frac{(1-\theta)^2}{4}\right) \int_{\Omega^n} \underbrace{\exp\left(\frac{\theta \mathcal{D}_{A(\omega)}^c(x)^2}{4}\right)}_X \underbrace{\exp\left(\frac{(1-\theta) \mathcal{D}_B^c(x)^2}{4}\right)}_Y dP(x) \\
& = \exp\left(\frac{(1-\theta)^2}{4}\right) \mathbb{E}[X \cdot Y] \\
& \leq \exp\left(\frac{(1-\theta)^2}{4}\right) \mathbb{E}[X^p]^{1/p} \mathbb{E}[Y^q]^{1/q}, \text{ (for } p = \frac{1}{\theta}, q = \frac{1}{1-\theta}: \theta \in [0, 1]) \\
& = \exp\left(\frac{(1-\theta)^2}{4}\right) \left(\int_{\Omega^n} \exp(\mathcal{D}_{A(\omega)}^c(x)^2/4) dP(x)\right)^\theta \left(\int_{\Omega^n} \exp(\mathcal{D}_B^c(x)^2/4) dP(x)\right)^{1-\theta} \\
& \leq \exp\left(\frac{(1-\theta)^2}{4}\right) \left(\frac{1}{P(A(\omega))}\right)^\theta \left(\frac{1}{P(B)}\right)^{1-\theta} \text{ by induction hypothesis.} \\
& = \exp\left(\frac{(1-\theta)^2}{4}\right) \frac{1}{P(B)} \left(\frac{P(A(\omega))}{P(B)}\right)^{-\theta} \tag{7}
\end{aligned}$$

(7) is true for any  $\theta \in [0, 1]$ , so for tightest upper bound, we shall optimize.

**Claim:** for any  $u \in [0, 1]$ ,  $\inf_{\theta \in [0,1]} \exp\left(\frac{(1-\theta)^2}{4}\right) u^{-\theta} \leq 2 - u$ .

Therefore, (7) reduces to

$$\leq \frac{1}{P(B)} \left(2 - \frac{P(A(\omega))}{P(B)}\right)$$

Therefore,

$$\begin{aligned}
& \int_{\Omega^{n+1}} \exp\left(\frac{\mathcal{D}_A^c(x,\omega)^2}{4}\right) dP(x) d\mu(\omega) \\
& \leq \frac{1}{\mathbb{P}(B)} \int_{\Omega} \left(2 - \frac{\mathbb{P}(A(\omega))}{\mathbb{P}(B)}\right) d\mu(\omega) \\
& \leq \frac{1}{\mathbb{P}(B)} \left(2 - \frac{(P \otimes \mu)(A)}{\mathbb{P}(B)}\right) \\
& \leq \frac{1}{(\mathbb{P} \otimes \mu)(A)}, \text{ (since } u(2-u) \leq 1 \text{ for all } u \in \mathbb{R}) \tag{8}
\end{aligned}$$

This completes the proof of Talagrand's inequality.

**Claim:**  $f(u) = u(2-u) \Rightarrow f'(u) = 2-2u \Rightarrow u^* = 1 \Rightarrow \max_u f(u) =$

$$f(1) = 1.$$

*Proof.* To establish:  $\inf_{\theta \in [0,1]} \exp\left(\frac{(1-\theta)^2}{4}\right)u^{-\theta} \leq 2 - u$ :

if  $u \geq e^{-1/2}$ :  $\theta = 1 + 2 \log u \Rightarrow \frac{1-\theta}{2} = -\log u \Rightarrow \frac{(1-\theta)^2}{4} = \log^2(u)$  and  $u^{-\theta} = e^{-\theta \log u} = e^{-\log u} e^{-2 \log^2 u}$ . Thus,

$$\exp\left(\frac{(1-\theta)^2}{4}\right)u^{-\theta} = \exp(\log^2 u - 2 \log^2 u - \log u) = \exp(-\log u - \log^2 u)$$

We have that

$$1 \geq u \geq e^{-1/2} \Rightarrow 0 \geq \log u \geq -\frac{1}{2} \Rightarrow 0 \leq -\log u \leq \frac{1}{2}, \quad 0 \leq \log^2 u \leq \frac{1}{4}$$

and

$$f(x) = -x - x^2 : x \in [-1/2, 0]; \quad f'(x) = -1 - 2x \leq 0 \text{ for } x \in [-1/2, 0]$$

Thus,

$$-\log u - \log^2 u \leq \frac{1}{2} - \frac{1}{4} \leq \frac{1}{4} \Rightarrow \exp(-\log u - \log^2 u) \leq \frac{1}{4}$$

and for  $u \geq e^{-1/2}$  which implies that  $2 - u \geq \exp(-\log u - \log^2 u)$ . □

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