Question 1

We have seen that for any $f: \{0,1\}^n \to \mathbb{R}$, there exists a *unique* multilinear polynomial P_f such that $P_f(x) = f(x)$ for all $x \in \{0,1\}^n$. Thus it suffices to give a multilinear polynomial that computes each function exactly.

• OR. We can write $x_1 \vee \ldots \vee x_n$ as $\neg(\bar{x_1} \wedge \ldots \wedge \bar{x_n})$. Hence we will use the multilinear polynomial of AND to obtain

$$
P_{OR}(x) = 1 - (1 - x_1)(1 - x_2) \dots (1 - x_n).
$$

Thus the exact degree of OR is n.

• PARITY. If our variables were ± 1 , then the product of the variables captures the parity exactly. Hence we will use the transformation $x \to 1-2x$ that maps $0 \rightarrow 1$ and $1 \rightarrow -1$ to obtain

$$
P_{PARITY}(x) = (1 - 2x_1)(1 - 2x_2) \dots (1 - 2x_n).
$$

Thus the exact degree of PARITY is n .

• MAJORITY. We will write the multilinear polynomial by considering all possible inputs. First, define the linear function

$$
\mathbf{1}_{z_i}(x_i) = \begin{cases} 1 - x_i & z_i = 0 \\ x_i & z_i = 1 \end{cases}
$$

that outputs 1 if the bits z_i, x_i are equal and 0 otherwise. Now we can easily write P_{MAJ} as a sum of 'indicators' as follows:

$$
P_{MAJ}(x) = \sum_{\substack{z \in \{0,1\}^n \\ \text{MAJ}(z) = 1}} \prod_{i=1}^n \mathbf{1}_{z_i}(x_i).
$$

Now we should show that P_{MAJ} has degree n. We just have to consider the coefficient of $x_1x_2 \ldots x_n$. It is easy to see that its coefficient is $\sum_{k=\lceil n/2 \rceil}^{n} (-1)^{n-k} \binom{n}{k}$ $\binom{n}{k}$ which is never equal to 0.

Question 2

The majority, as we have seen, is a function whose block sensitivity is not equal to its exact degree. Recall that its block sensitivity was $\lceil n/2 \rceil$, whereas its degree is equal to n.

Question 3

We have seen how we can represent a classical query algorithm $\mathcal A$ (deterministic or randomized) via a decision tree. If this algorithm makes q queries to its input, then this decision tree has depth at most q . Every leaf of the decision tree v is assigned the value $A(v)$, which is the output of the algorithm in that branch.

For simplicity, we will use the following linear function

$$
\mathbf{1}_{z_i}(x_i) = \begin{cases} 1 - x_i & z_i = 0 \\ x_i & z_i = 1 \end{cases}.
$$

Note that $\mathbf{1}_{z_i}(x_i) = 1$ iff $x_i = z_i$. We can then write down a polynomial that has a term for every such leaf. We will represent with $path(v)$ the set of variables and their values in the path to leaf v . Then the polynomial is

$$
P(x) = \sum_{\text{leaf } v} \mathcal{A}(v) \prod_{(x_i, b_i) \in \text{path}(v)} \mathbf{1}_{b_i}(x_i).
$$

Since the path to each leaf contains at most q variables, $P(x)$ is a multilinear polynomial with degree at most q.

Now, if A is a deterministic algorithm, then the number of queries is at most $D(f)$ and the algorithm always succeeds, hence $P(x) = f(x)$. We conclude that $\deg(f) \le D(f)$. For a randomized A, the number of queries is at most $R(f)$ and the algorithm succeeds with probability at least $\frac{2}{3}$, thus the same polynomial is actually an approximation $\tilde{P}(x)$ to $f(x)$ that satisfies $|\tilde{P}(x) - f(x)| \leq \frac{1}{3}$. We conclude that $R(f) \leq d \tilde{eg}(f)$.

Question 1

Consider the multivariate polynomial $P(x_1, \ldots, x_n)$ that approximates OR of minimal degree. As in the lecture, we define with B_k to be the set of inputs with Hamming weight k . We will define

$$
P_{sym}(k) = \mathop{\mathbb{E}}_{x_1,\dots,x_n \sim B_k} P(x_1,\dots,x_n).
$$

Since P approximates OR, it should hold that

 $\int P_{sym}(0) \in [0, \frac{1}{3}]$ $\frac{1}{3}$ $P_{sym}(k) \in \left[\frac{2}{3}\right]$ $\left[\frac{2}{3}, 1\right]$ $k \in \{1, \ldots, n\}.$

Also note that P_{sym} 'jumps' from at most $\frac{1}{3}$ to at least $\frac{2}{3}$ from 0 to 1. Hence there must exist some $x \in [0, 1]$ such that $P'_{sym}(x) \geq \frac{1}{3}$ $\frac{1}{3}$ by the mean value theorem. This allows us to use the Ehlich, Zeller and Rivlin, Cheney inequality with $a = 0, b = 1, c = \frac{1}{3}$ $\frac{1}{3}, k = n.$ This implies that $\deg(P_{sym}) \geq \sqrt{\frac{n}{3}}$.

This already implies that

$$
Q(OR) \ge \frac{\deg(OR)}{2} = \frac{\deg(P)}{2} \ge \frac{\deg(P_{sym})}{2} \ge \Omega(\sqrt{n}).
$$

Question 2.1

Let P be a multilinear polynomial that approximates PARITY. We will define the univariate polynomial Q to be as follows:

$$
Q(k) = \mathbb{E}_{\substack{x \in \{0,1\}^n \\ \sum_i x_i = k}} [1 - 2P(x)].
$$

Note that $\deg(Q) \leq \deg(P)$ and for any x with odd Hamming weight k we have that $|P(x) - 1| \leq \frac{1}{3} \implies |Q(k) - (-1)| \leq \frac{2}{3}$, and for any x with even Hamming weight k $|P(x)-0| \leq \frac{1}{3}$ \implies $|Q(k)-1| \leq \frac{2}{3}$. Thus $Q(k)$ approximates Sign(k) up to $\frac{2}{3}$ additive error.

Question 2.2

This polynomial $Q(k)$ is positive when k is even and negative and k is odd for all $k \in \{0, \ldots, n\}$. This means that it has at least n distinct roots from the mean value theorem, which implies that the degree of Q must be at least n.

Combining with the previous question we conclude that $deg(PARTY) = n$ and thus $Q(f) \geq \frac{n}{2}$ $\frac{n}{2}$.

Question 3

Let \tilde{P}_n be the polynomial that achieves the deg for PALINDROME with n inputs (n is even). Consider the following polynomial

$$
P_{sym}(x_1,\ldots,x_n) = 1 - \tilde{P}_{2n}(0,\ldots,0,x_n,\ldots,x_1)].
$$

One can verify that $0 \dots 0 x_n \dots x_1$ is a palindrome iff $OR(x_1, \dots, x_n) = 0$, thus $P_{sum}(x)$ approximates the OR function. now note that the degree of P_{sym} is at most the approximate degree of PALINDROME on $2n$ inputs. Since the approximate degree of OR is $\Omega(\sqrt{n})$, we deduce that $\deg(PAL) = \Omega(\sqrt{n})$ as well.

Question 4

Similar to the previous question, we will embed OR inside the polynomial that approximates f. Let \tilde{P}_n be the polynomial that achieves the deg for f with n inputs and let y be an input that achieves the maximal number of sensitive blocks B_1, \ldots, B_k . For simplicity let $k = bs(f)$. Consider the following polynomial

$$
P_{sym}(x_1,\ldots,x_k)=1-\tilde{P}_n(y^x).
$$

Here we define y^x to be equal to y with the coordinates in B_i flipped if $x_i = 1$. This can be represented as $x_i(1-y_j) + (1-x_i)y_j$ if coordinate $j \in B_i$.

Now note that P_{sym} can distinguish between the all-zeros input 0 and the inputs with hamming weight exactly one **i** from Lecture 1. Using a symmetrization argument, no matter the values of P_{sum} for the rest of the inputs, it must hold that the degree no matter the values of P_{sym} for the rest of the inputs, it must note that the degree
of P_{sym} is at least $\Omega(\sqrt{k}) = \Omega(\sqrt{bs(f)})$. Since $\tilde{P}_n(y^x)$ has the same degree as $\tilde{P}_n(y)$, it must hold

Question 1

Primal. We will represent the degree-(d) polynomial using its coefficients $\{\alpha_S\}_{S\subseteq[n]}$ as:

$$
P(x) = \sum_{\substack{S \subseteq [n] \\ |S| < d}} \alpha_S x^S,
$$

where we define $x^S = \prod_{i \in S} x_i$. Hence the primal becomes:

$$
\min_{\epsilon, \{\alpha_S\}_S} \epsilon
$$
\n
$$
\text{s.t.} \sum_S \alpha_S x^S - f(x) \le \epsilon \qquad \forall x \in \{-1, 1\}^n
$$
\n
$$
\sum_S \alpha_S x^S - f(x) \ge -\epsilon \qquad \forall x \in \{-1, 1\}^n
$$

We will convert it into standard form using some well-known tricks. First, we will replace the unconstrained coefficients with non-negative ones as follows:

$$
\alpha_S:=\alpha_S^+-\alpha_S^-.
$$

Additionally, we will change the right hand side variables to be non-negative by changing the sign of both sides. Finally, we change the inequalities to equalities by introducing slack variables, e.g.

$$
\sum_{S} \alpha_{S} x^{S} - f(x) + \xi_{x} = \epsilon.
$$

The final format is:

$$
\min \epsilon
$$
\n
$$
\epsilon
$$
\n
$$
\text{s.t.} \sum_{S} (\alpha_S^+ - \alpha_S^-) x^S - f(x) + \xi_x = \epsilon \qquad \forall x \in \{-1, 1\}^n
$$
\n
$$
\sum_{S} -(\alpha_S^+ - \alpha_S^-) x^S + f(x) + \psi_x = -\epsilon \qquad \forall x \in \{-1, 1\}^n
$$
\n
$$
\epsilon, \{\alpha_S^{\pm}\}_S, \{\xi_x\}_x, \{\psi_x\}_x \ge 0
$$

Dual. We will first show that we can 'relax' the second condition to $\sum_{x} |\phi(x)| \leq 1$, $\sum_{x} |\phi(x)| < 1$, then we can obtain $\phi'(x)$, which is scaled up to make the inequality without changing the optimal value. This is because if there exists some ϕ with tight. By scaling up to $\phi'(x)$, we are also scaling the objective value, which will give us something larger. This is because the optimal of the dual is always non-negative. Thus we will convert the following program into standard form:

$$
\max_{\phi} \sum_{x} \phi(x) \cdot f(x)
$$

s.t.
$$
\sum_{x} |\phi(x)| \le 1
$$

$$
\sum_{x} \phi(x) \cdot P(x) = 0 \qquad \forall P, \deg(P) < d
$$

We will follow the same recipe as the primal. Write the polynomial ϕ as

$$
\phi(x) = \sum_{\substack{S \subseteq [n] \\ |S| \ge d}} (\beta_S^+ - \beta_S^-) x^S.
$$

Now we will write the $\sum_{x} |\phi(x)| \leq 1$ by bounding each term separately, i.e.

$$
|\phi(x)| \leq \gamma_x \implies -\gamma_x \leq \phi(x) \leq \gamma_x, \ \forall \ x \in \{\pm 1\}^n,
$$

and imposing the condition that $\sum_{x} \gamma_x = 1$.

The final format is:

$$
\max \sum_{x} \left[\sum_{\substack{S \subseteq [n] \\ |S| \ge d}} (\beta_S^+ - \beta_S^-) x^S \right] \cdot f(x)
$$
\n
$$
\text{s.t.} \sum_{\substack{S \subseteq [n] \\ |S| \ge d}} (\beta_S^+ - \beta_S^-) x^S + \xi_x = \gamma_x \qquad \forall x \in \{\pm 1\}^n
$$
\n
$$
- \sum_{\substack{S \subseteq [n] \\ |S| \ge d}} (\beta_S^+ - \beta_S^-) x^S + \phi_x = \gamma_x \qquad \forall x \in \{\pm 1\}^n
$$
\n
$$
\sum_{\substack{x \\ |S| \ge d}} \gamma_x = 1
$$
\n
$$
\{\beta_S^{\pm}\}_S \ge 0, \{\xi_x\}_x \ge 0, \{\phi_x\}_x \ge 0, \{\gamma_x\}_x \ge 0
$$

Question 2

The dual polynomial certificate is $\phi(x) = \frac{1}{2^n} x_1 \dots x_n$. It is easy to see that $\phi(x) =$ $\frac{1}{2^n}f(x)$, and thus

$$
\sum_{x \in \{\pm 1\}^n} \phi(x) \cdot f(x) = 1.
$$

Additionally, we can check that $\sum_{x} |\phi(x)| = 2^n \cdot \frac{1}{2^n} = 1$, and ϕ has no monomial of degree $\langle n$. Thus, by weak duality PARITY = n.

Question 1

Since the marginal distribution $D_{|S}$ is uniform over $\{0,1\}^{|S|}$ for any k-wise independent distribution D, any randomized algorithm that makes less than $k + 1$ queries will just see a uniform set of bits.

Hence the view of the algorithm is the same for both distributions. Thus the algorithm cannot distinguish between the two distributions.

Question 2

Consider a quantum query algorithm A that makes less than $k + 1$ queries and outputs 1 if it thinks its input $x \in \{0,1\}^n$ was drawn from D and 0 otherwise.

We construct the polynomial $p(x)$ that captures the probability that A outputs 1 on input x. Since A makes $\leq k$ queries, then $p(x)$ has degree at most 2k. Write $p(x)$ as:

$$
p(x) = \sum_{\substack{S \subseteq [n] \\ |S| \le 2k}} \alpha_S x^S.
$$

Then the expected behavior of A for x drawn from D is

$$
\mathbb{E}_{x \sim D}[\mathcal{A}(x)] = \mathbb{E}_{x \sim D}[p(x)]
$$
\n
$$
= \mathbb{E}_{x \sim D} \left[\sum_{\substack{S \subseteq [n] \\ |S| \le 2k}} \alpha_S x^S \right]
$$
\n
$$
= \sum_{\substack{S \subseteq [n] \\ |S| \le 2k}} \alpha_S \mathbb{E}_{x \sim D}[x^S]
$$

Now note that since D is a 2k-wise independent distribution, it means that the

distribution of any $\leq 2k$ bits is equal to the uniform distribution. Thus we can write

$$
\mathbb{E}_{x \sim D}[\mathcal{A}(x)] = \sum_{\substack{S \subseteq [n] \\ |S| \le 2k}} \alpha_S \mathbb{E}_{x \sim \mathcal{U}}[x^S]
$$

$$
= \mathbb{E}_{x \sim \mathcal{U}}[p(x)]
$$

$$
= \mathbb{E}_{x \sim \mathcal{U}}[\mathcal{A}(x)].
$$

As a result, \mathcal{A} 's output distribution is the same when given input from D or U. Thus no quantum query algorithm can distinguish between U and D .