

Exams

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with Norm Beaudry, Frédéric Dupuis and Renato Renner

Randomness for testing

Randomness used to test a property
(specific state, Bell violation,...)

- Many systems $Y_1 \dots Y_n$
- Want: testing random subset enough to guarantee global property

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Another property we would like to test:

Has student B learned the data $X_1 \dots X_n$?

- Want: testing random subset enough to guarantee global learning

Probabilistic model

Systems:

- Data: $X_1, \dots, X_n \in \{0, 1\}^n$
- Student memory: B (could be classical or quantum)

Modeled by a joint distribution $P_{X_1 \dots X_n B}$

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Test:

- Exam: $\vec{i} = (i_1, \dots, i_k)$ with $i_p \in \{1, \dots, n\}$
- Given B and \vec{i} , answer $A^{\vec{i}} = A^{\vec{i}}(B, \vec{i}) \in \{0, 1\}^k$
- Grade given by $\mathbf{G}_k = \sum_{p=1}^k \mathbf{1}_{X_{i_p} = A_p^{\vec{i}}} = k - d_H(X_{\vec{i}}, A^{\vec{i}})$

Property we are testing: correlation between B and $X_1 \dots X_n$

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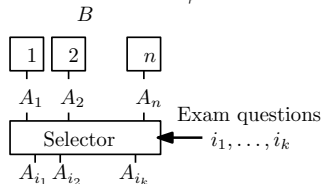
Think of the student as the adversary

Exam strategies

Notation: Data: $X_1 \dots X_n \in \{0, 1\}^n$ Exam: $\vec{i} = (\vec{i}_1, \dots, \vec{i}_k)$ with $\vec{i}_p \in \{1, \dots, n\}$

Student memory B Answer $A^{\vec{i}} = A^{\vec{i}}(B, \vec{i}) \in \{0, 1\}^k$ Grade $G_k(A^{\vec{i}}) = \sum_{p=1}^k \mathbf{1}_{X_{\vec{i}_p} = A_p^{\vec{i}}}$

Special kind of strategy:
Simple strategies

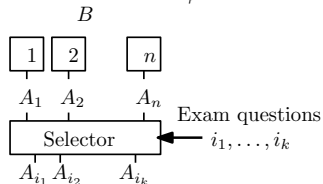


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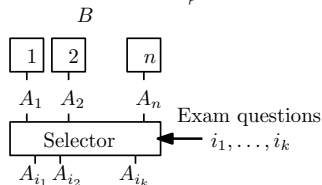
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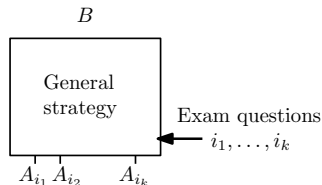
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Special kind of strategy:
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General strategy
described by $\{A^{\vec{i}}\}_{\vec{i}}$



In general strategies, answer to question i **depends on context**

Desired statement

Notation: Data: X_1, \dots, X_n

Student memory contains B

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Example: X uniform on $\{0, 1\}^n$ and

$$B = \begin{cases} X & \text{with prob. } 1/2 \\ 0 & \text{with prob. } 1/2 \end{cases}$$

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Property we are looking after:

memory B allows answering many X_1, \dots, X_n correctly

Theorem

For any $P_{X_1 \dots X_n B}$ and any $\{A^{\vec{i}}\}_{\vec{i}}$, there exists an $\bar{A} = \bar{A}(B, \vec{i}, X_{\vec{i}}) \in \{0, 1\}^n$ s.t.

$$\mathbf{P} \left\{ \frac{G_n(\bar{A})}{n} \leq \frac{G_k(A^{\vec{i}})}{k} - \delta \right\} \leq e^{-\frac{\delta^2 k}{32}}$$

Exam: simple strategies

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For **simple strategies**, $A_{i_p}^{\vec{i}} = A_{i_p}$ for some $A \in \{0, 1\}^n$

We choose $\bar{A} = A$. Statement becomes

Theorem

For any random variable $A = A_1 \dots A_n$,

$$\mathbf{P}_{\vec{i}, X, A} \left\{ \frac{1}{n} \sum_{\ell=1}^n \mathbf{1}_{X_{\ell} = A_{\ell}} \leq \frac{1}{k} \sum_{p=1}^k \mathbf{1}_{X_{i_p} = A_{i_p}} - \delta \right\} \leq e^{-\frac{\delta^2 k}{32}}$$

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For fixed X and A : standard bounds on hypergeometric distribution

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For any strategy $\{A^{\vec{i}}\}_{\vec{i}}$, there exists an $\bar{A} = \bar{A}(B, \vec{i}, X_{\vec{i}})$ such that

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- Choose $\bar{A}_\ell = \text{MAJ}\{A_\ell^{\vec{j}} : \ell \in \vec{j}\}$

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Proof: introducing sequential exams

Notation: $\vec{p}^{-1} = \vec{i}_1, \dots, \vec{i}_{p-1}$

Two steps:

- 1 Introduce “sequential exams” and prove statement
- 2 Relate general strategies for a strategy for sequential exam

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Sequential exam (or oral exam)

Interaction between examiner and student

- Questions one by one
- Have to answer \vec{i}_p before getting \vec{i}_{p+1}
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$\rightarrow A_p^{\text{seq}} = A_p^{\text{seq}}(\vec{i}_p, \vec{i}^{p-1}, X_{\vec{i}^{p-1}})$ but independent of $\vec{i}_{p+1} \dots \vec{i}_k$

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Remark: A priori “general” and “sequential” incomparable

Proof for sequential strategies

Theorem

For any sequential strategy A^{seq} , there exists an $\bar{A} = \bar{A}(B, \vec{i}, X_{\vec{i}})$ such that

$$\mathbf{P} \left\{ \frac{\mathbf{G}_n(\bar{A})}{n} \leq \frac{\mathbf{G}_k(A^{\vec{i}})}{k} - \delta \right\} \leq e^{-\frac{\delta^2 k}{8}}$$

Simplification: define \bar{A} only on \vec{j} with $|\vec{j}| = k$

→ look at $\left[\frac{\mathbf{G}_k(\bar{A})}{k} \leq \frac{\mathbf{G}_k(A^{\text{seq}})}{k} - \delta \right]$

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$$\bar{A}_{\vec{j}_p} \stackrel{\text{def}}{=} A_p^{\text{seq}}(\vec{j}_p, \vec{i}^{p-1}, X_{\vec{i}^{p-1}})$$

To answer all questions: Partition $[n] = S_1 \cup \dots \cup S_k$ at random, and for $\ell \in S_p$, let

$$\bar{A}_\ell = A^{\text{seq}}(\ell, \vec{i}^{p-1}, X_{\vec{i}^{p-1}})$$

Proof for sequential strategies

Notation: $\vec{i}^{p-1} = \vec{i}_1, \dots, \vec{i}_{p-1}$ Grade $G_k(A^{\text{seq}}) = \sum_{p=1}^k \mathbf{1}_{X_{\vec{i}_p} = A_p}^{\text{seq}}$ Grade $G_k(\bar{A}) = \sum_{p=1}^k \mathbf{1}_{X_{\vec{j}_p} = \bar{A}_p}$

Using Azuma's inequality:

$$\mathbf{P} \left\{ \sum_{p=1}^k \mathbf{1}_{X_{\vec{i}_p} = A_p}^{\text{seq}} - \sum_{p=1}^k \mathbf{E}_{\vec{i}_p, X_{\vec{i}_p}} \left\{ \mathbf{1}_{X_{\vec{i}_p} = A_p}^{\text{seq}} \left| \vec{i}^{p-1} \vec{j}^{p-1} X_{\vec{i}^{p-1}} X_{\vec{j}^{p-1}} \right. \right\} \geq \delta k \right\} \leq e^{-\frac{\delta^2 k}{2}}$$

$$\mathbf{P} \left\{ \sum_{p=1}^k \mathbf{E}_{\vec{j}_p, X_{\vec{j}_p}} \left\{ \mathbf{1}_{X_{\vec{j}_p} = \bar{A}_p} \left| \vec{i}^{p-1} \vec{j}^{p-1} X_{\vec{i}^{p-1}} X_{\vec{j}^{p-1}} \right. \right\} - \sum_{p=1}^k \mathbf{1}_{X_{\vec{j}_p} = \bar{A}_p} \geq \delta k \right\} \leq e^{-\frac{\delta^2 k}{2}}$$

Observe:

$$\mathbf{E} \left\{ \mathbf{1}_{X_{\vec{i}_p} = A_p}^{\text{seq}} \left| \vec{i}^{p-1} \vec{j}^{p-1} X_{\vec{i}^{p-1}} X_{\vec{j}^{p-1}} \right. \right\} = \mathbf{E} \left\{ \mathbf{1}_{X_{\vec{j}_p} = \bar{A}_p} \left| \vec{i}^{p-1} \vec{j}^{p-1} X_{\vec{i}^{p-1}} X_{\vec{j}^{p-1}} \right. \right\}$$

$$\Rightarrow \mathbf{P} \left\{ \sum_{p=1}^k \mathbf{1}_{X_{\vec{i}_p} = A_p}^{\text{seq}} - \sum_{p=1}^k \mathbf{1}_{X_{\vec{j}_p} = \bar{A}_p} \geq 2\delta k \right\} \leq 2e^{-\frac{\delta^2 k}{2}}$$

Relating general to sequential strategies

Theorem

There exists A^{seq} such that for any $\{A_p^{\vec{i}}\}$

$$\mathbf{P} \left\{ \sum_{p=1}^k \mathbf{1}_{X_{i_p}^{\vec{i}} = A_p^{\vec{i}}} - \sum_{p=1}^k \mathbf{1}_{X_{i_p}^{\vec{i}} = A_p^{\text{seq}}} \geq \delta k \right\} \leq e^{-\frac{\delta^2 k}{8}}$$

$A^{\text{seq}}(\ell, \vec{i}^{\ell-1}, X_{\vec{i}^{\ell-1}}) \stackrel{\text{def}}{=} \text{best guess for } X_\ell \text{ given } B, \vec{i}^{\ell-1}, X_{\vec{i}^{\ell-1}}$

$$\text{Azuma} \quad \Rightarrow \quad \sum_{p=1}^k \mathbf{1}_{X_{i_p}^{\vec{i}} = A_p^{\vec{i}}} \approx \sum_{p=1}^k \mathbf{E}_{\vec{i}_p, X_{\vec{i}_p}^{\vec{i}}} \left\{ \mathbf{1}_{X_{i_p}^{\vec{i}} = A_p^{\vec{i}}} \middle| \vec{i}^{\ell-1}, X_{\vec{i}^{\ell-1}} (A^{\vec{i}})^{p-1} \right\}$$

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For any fixed \vec{i}_p and B , $(A^{\vec{i}})^{p-1}$ cannot help in predicting $X_{\vec{i}_p}$

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Recap of the proof

Start with $\{A^{\vec{i}}\}_{\vec{i}}$

A^{seq} (guesses optimally given past) is at least as good on exam \vec{i}

If A^{seq} works on \vec{i} , also works on rest

Theorem

For any strategy $\{A^{\vec{i}}\}_{\vec{i}}$, there exists an $\bar{A} = \bar{A}(B, \vec{i}, X_{\vec{i}})$ such that

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System B is quantum

Important difficulty: Applying $A^{\vec{i}}(B, \vec{i})$ affects B

Issues in the two steps of the classical proof

- 1 For sequential strategies, measurement may lead to losses
- 2 Cannot simultaneously define the two strategies

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Better way of quantifying correlation:

- Use $H_{\max}(X_1 \dots X_n | B)$ (number of bits of hint for perfect recovery of $X_1 \dots X_n$)