Fully Adaptive Framework: Neural Computerized Adaptive Testing for Online Education

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Background

**Typical CAT procedure.**

1. **Cognitive Diagnosis Model (CDM)**, which first estimates the student’s current proficiency $\hat{\theta}_t$ based on previous $t$ responses. The representative models are IRT and NCDM.

2. **Selection Algorithm** then selects the next question, guided by his/her current proficiency estimate $\hat{\theta}_t$ above. Most algorithms are **model-specific**, which are specially designed by experts according to different CDMs’ characteristics.

**Goal:**
- Measuring student’s proficiency accurately
- Reducing test length
Background

How to **accurately** and **efficiently** measure student’s ability/proficiency?

- Paper-and-pencil Examination
  - Too many questions - inefficient and boring
  - Fixed time/place - inflexible

- Computerized Adaptive Testing (CAT)
  - Personalization and reduce test length
  - Flexible time/place
Background

Typical CAT procedure.

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- Reducing test length

(1) Cognitive Diagnosis Model (CDM), which first estimates the student’s current proficiency $\hat{\theta}^t$ based on previous $t$ responses. The representative models are IRT and NCDM.

(2) The Selection Algorithm then selects the next question, guided by his/her current proficiency estimate $\hat{\theta}^t$ above. Most algorithms are model-specific, which are specially designed by experts according to different CDMs’ characteristics.
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Typical CAT procedure.

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Limited adaptability:
- For student, selection algorithm’s efficiency heavily relies on the accuracy of $\hat{\theta}^t$.
- For CDM, have to understand how a specific CDM works to design the matched algorithms.
- For questions, such pre-defined algorithms have individual “preference” in selections (e.g., MFI).

→ Poor robustness, Loss of information
→ Model-specific, Labor-intensive
→ Exposure unbalance, Test insecurity
Outline

1. Background
2. Formulation
3. Implementation
4. Experiment
5. Conclusion
The Learnable Selection Algorithm $\pi$: Bi-level Optimization

The responses of student $i$ is randomly divided into:

1. Support set $D_s^i$
2. Query set $D_u^i$

Outer-level

$$\pi^* = \arg \min \pi \, \frac{1}{n} \sum_{i=1}^{n} \sum_{t=1}^{T} \frac{1}{|D_u^i|} \sum_{(q,a) \in D_u^i} l(a, \mathcal{M}(q|\hat{\theta}_i^t)), $$

s.t. $\hat{\theta}_i^t = \arg \min \theta_i \sum_{(q,a) \in D_s^{i(t)}} l(a, \mathcal{M}(q|\theta_i)),$

Inner-level

where $D_s^{i(t)} = \{q_1, a_{i(1)}, \ldots, q_t, a_{i(t)}\}$ and

$q_t \sim \pi \left( q_1, a_{i(1)}, \ldots, q_{t-1}, a_{i(t-1)} \right).$
Formulation

**The Learnable Selection Algorithm $\pi$:**

**Bi-level Optimization**

The responses of student $i$ is randomly divided into:

1. Support set $D_s^i$
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**Outer-level**

$$\pi^* = \arg\min_{\pi} \frac{1}{n} \sum_{i=1}^{n} \sum_{t=1}^{T} \frac{1}{|D_u^i|} \sum_{(q,a) \in D_u^i} l(a, M(q|\hat{\theta}_i^t)),$$

s.t. $\hat{\theta}_i^t = \arg\min_{\theta_i} \sum_{(q,a) \in D_s^i(t)} l(a, M(q|\theta_i))$,

where $D_s^i(t) = \{q_1, a_{i(1)}, \ldots, q_t, a_{i(t)}\}$ and $q_t \sim \pi(q_1, a_{i(1)}, \ldots, q_{t-1}, a_{i(t-1)}).$

**Using large-scale response data**
The Learnable Selection Algorithm $\pi$: Using large-scale response data

Bi-level Optimization

The responses of student $i$ is randomly divided into:

(1) Support set $D_s^i$  (2) Query set $D_u^i$

Outer-level

Fit of estimate on query set

Proficiency estimate on support set

Inner-level

Sum all the test steps and students

$\pi^* = \arg\min_{\pi} \frac{1}{n} \sum_{i=1}^{n} \sum_{t=1}^{T} \frac{1}{|D_u^i|} \sum_{(q,a) \in D_u^i} l(a, \mathcal{M}(q|\hat{\theta}_i^t)),

\text{s.t.} \left\{ \hat{\theta}_i^t = \arg\min_{\theta_i} \sum_{(q,a) \in D_s^{i(t)}} l(a, \mathcal{M}(q|\theta_i)), \right\}

where $D_s^{i(t)} = \{q_1, a_{i(1)}, \ldots, q_t, a_{i(t)}\}$ and $q_t \sim \pi (q_1, a_{i(1)}, \ldots, q_{t-1}, a_{i(t-1)}).$
Formulation

◆ The Learnable Selection Algorithm $\pi$:

◆ Reinforcement Learning Formulation

$$
\min_{\pi} \frac{1}{n} \sum_{i=1}^{n} \sum_{t=1}^{T} \frac{1}{|\mathcal{D}_i^u|} \sum_{(q,a) \in \mathcal{D}_i^u} l(a, \mathcal{M}(q|\hat{\theta}_i^t)) \\
\triangleq \max_{\pi} \mathbb{E}_{i \sim \pi} \left[ \sum_{t=1}^{T} \frac{1}{|\mathcal{D}_u^i|} \sum_{(q,a) \in \mathcal{D}_u^i} l(a, \mathcal{M}(q|\hat{\theta}_i^t)) \right] \\
= \max_{\pi} \mathbb{E}_{i \sim \pi} \left[ \sum_{t=1}^{T} -\mathcal{L} \mathcal{M}(\mathcal{D}_u^i, \hat{\theta}_i^t) \right],
$$
The Learnable Selection Algorithm $\pi$:

Reinforcement Learning Formulation

\[
\min_\pi \frac{1}{n} \sum_{i=1}^{n} \sum_{t=1}^{T} \frac{1}{|\mathcal{D}_u^i|} \sum_{(q,a) \in \mathcal{D}_u^i} l(a, \mathcal{M}(q|\hat{\theta}_i^t))
\]

\[
\triangleq \max_\pi \mathbb{E}_{i \sim \pi} \left[ \sum_{t=1}^{T} -\frac{1}{|\mathcal{D}_u^i|} \sum_{(q,a) \in \mathcal{D}_u^i} l(a, \mathcal{M}(q|\hat{\theta}_i^t)) \right]
\]

\[
= \max_\pi \mathbb{E}_{i \sim \pi} \left[ \sum_{t=1}^{T} \frac{-\mathcal{L}_\mathcal{M}(\mathcal{D}_u^i, \hat{\theta}_i^t)}{\text{Reward}} \right]
\]

- **State**: previous $t$ responses
  
  \[ s_t = \{q_1, a_{i(1)}, ..., q_{t-1}, a_{i(t-1)}\} \].

- **Action**: selection of next question: $q_t$

- **Transition**: the uncertainty comes from next question’s correction $a_{i(t)}$
  
  \[ P(s_{t+1}|s_t, q_t) \]

- **Reward**: negative loss of the estimated proficiency of on query set
  
  \[ -\mathcal{L}_\mathcal{M}(\mathcal{D}_u^i, \hat{\theta}_i^t) \]
The Learnable Selection Algorithm $\pi$:

**Reinforcement Learning Formulation**

- **State**: previous $t$ responses
  
  $$s_t = \{q_1, a_{i(1)}, \ldots, q_{t-1}, a_{i(t-1)}\}.$$  

- **Action**: selection of next question: $q_t$

- **Transition**: the uncertainty comes from next question’s correction $a_{i(t)}$
  
  $$P(s_{t+1} | s_t, q_t)$$

- **Reward**: negative loss of the estimated proficiency of on query set
  
  $$-\mathcal{L}_M(D_u^i, \hat{\theta}_i^t)$$

**Diagram:**

- Selection Algorithm
  - Observe
  - Student Response data
  - Reward
  - Selection
  - Query Set
    - Proficiency estimate
    - Outer-level Optimization
  - Cognitive Diagnosis Model
    - Inner-level Optimization
- CAT ➔ Reinforcement Learning problem
Outline

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Methodology

◆ Selection algorithm in our NCAT framework:
  ◆ Double-Channel Performance Learning
  ◆ Contradiction Learning
◆ Selection algorithm in our NCAT framework:

◆ Double-Channel Performance Learning

Correct and incorrect responses are imbalanced: incorrect < correct

Separately capture the information of versatile student performance (double-channel)
Methodology

Selection algorithm in our NCAT framework:

Contradiction Learning

Contradictions between the correct and incorrect responses:

- Guess factor in the harder
- Slip factor in the simpler
- Both

Possible Contradiction:
- Guess factor in the harder
- Slip factor in the simpler
- Both
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## Experiment

### Setups

- **Dataset**
  - Real-world datasets from three **online tutoring system**
  - Involving two classic CDM: **IRT** and **NCDM**

- **Comparison Methods**
  - **Traditional information/uncertainty-based:**
    - MFI, KLI
    - MAAT (active learning)
  - **Meta Learning:**
    - BOBCAT

- **Evaluation Metrics:** AUC, ACC, MSE
Our proposed NCAT achieves the best performance on all datasets and all types of CDMs.

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<th>Dataset</th>
<th>ASSIST</th>
<th>NIPS-EDU</th>
<th>EXAM</th>
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<tr>
<td>CDM</td>
<td>IRT</td>
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<tr>
<td>Step</td>
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<td>ACC</td>
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<th>NCDM</th>
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<td>–</td>
<td>–</td>
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<tr>
<td>KLI</td>
<td>0.7004</td>
<td>0.7104</td>
<td>0.7316</td>
<td>–</td>
<td>–</td>
<td>–</td>
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<tr>
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<td>0.7391</td>
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</table>
Experiment

Contradiction in Responses

Correct | Related Concepts                  | Difficulty
--------|-----------------------------------|------------
q1370   | Unary Linear Inequality           | 0.069      
qu918  | Real Number                        | 0.150      
qu2335 | Linear Equations in Three Variables| 0.171      
qu1368 | Cube Root                           | 0.140      

Incorrect | Related Concepts                  | Difficulty
-----------|-----------------------------------|------------
q2348      | Linear Equation in One Variable   | 0.151      
qu4804     | Function                           | 0.164      
qu8         | Real Number                         | 0.154      

Test Process
Experiment

Contradiction in Responses

Test Process

Correct | Related Concepts | Difficulty
---|---|---
q1370 | Unary Linear Inequality | 0.069
q918 | Real Number | 0.150
q2335 | Linear Equations in Three Variables | 0.171
q1368 | Cube Root | 0.140

Incorrect | Related Concepts | Difficulty
---|---|---
q2348 | Linear Equation in One Variable | 0.151
q4804 | Function | 0.164
q8 | Real Number | 0.154
Experiment

Contradiction in Responses

He answers a difficult question (q2335) correctly, but get a simple one wrong (q2348)

These observations imply that NCAT provides a good way to capture the complex relationship in questions-students for better selections.
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Formally redefine CAT as the Reinforcement Learning problem.
- No need to design the selection algorithm manually

Propose a novel Contradiction Learning module to model complex interactions
- Capture the Guess and Slip factors

Conduct extensive experiments with real-world educational datasets
- Efficiency, Robustness, Diversity, Exposure Rate
Thanks for your listening!

For more details, please refer to our paper!

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