Debugging Machine Learning Models

Emmanuel Charleson Dapaah
Prof. Jens Grabowski

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Outline

- Motivation
- Proposed Framework
- Future Works
- Conclusion
Motivation

Testing of Trustworthy Systems

Motivation

Debugging hyperparameter misconfigurations of an ML model using causal reasoning

https://towardsdatascience.com/the-ultimate-guide-to-debugging-your-machine-learning-models-103dc0f9e421
Motivating Example

Misconfiguration

```python
model = RandomForestClassifier(bootstrap=True,
max_depth=2,
max_features='auto',
min_samples_leaf=1,
min_samples_split=2,
n_estimators=30,
criterion='gini',
random_state=42)
```

Accuracy: 0.60

Hyperparameter Optimization

```python
model = RandomForestClassifier(bootstrap=False,
max_depth=10,
max_features='auto',
min_samples_leaf=1,
min_samples_split=2,
n_estimators=400,
criterion='gini',
random_state=42)
```

Accuracy: 0.88

Can be costly/time-consuming

Debugging

- Root cause
- Reduce the search space
- Interpretability/Explainability

User Hyperparameter Grid

New User Hyperparameter Grid

- Reduce the search space
- Interpretability/Explainability
Proposed Framework (Overview)

Input → Data Generation Process → Root Cause Analysis → Optimization
Proposed Framework (Data Generation Process)

**Input**
- Dataset
- Learning Algorithm
- User Hyperparameter Grid
- Number of Iterations

**Generate Observational data**

**Causality & ML Knowledge**

**Generate Causal Graph**

<table>
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<th>bootstrap</th>
<th>criterion</th>
<th>max_depth</th>
<th>max_features</th>
<th>min_samples_leaf</th>
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<td>10</td>
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</tr>
</tbody>
</table>
Proposed Framework

- Input
  - Observational data
  - Causal graph

Data Generation Process → Root Cause Analysis → Optimization

Testing of Trustworthy Systems #UCAAT
Proposed Framework (Root Cause Analysis)

**Average Causal Effect (ACE)**

\[ dE(Y|do(X=u))/du \]

1. **Compute ACE**
   - \( h_1 \)
   - \( h_2 \)
   - \( h_3 \)
   - \( h_4 \)
   - \( h_5 \)
   - \( h_6 \)
   - \(-0.5\)
   - \(0.2\)
   - \(0.8\)
   - \(-0.04\)
   - \(0.1\)

2. **ACE > threshold**
   - \( h_1 \)
   - \( h_2 \)
   - \( h_3 \)
   - \( h_4 \)
   - \( h_5 \)
   - \( h_6 \)
   - \(-0.5\)
   - \(0.8\)

**TAKE-AWAY**
- Identify the root causes
- Infer the tuning direction

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Observational Data → Causal Graph → Average Causal Effect (ACE) → Compute ACE → ACE > threshold → Root Cause
Proposed Framework

Input

Data Generation Process

Root Cause Analysis

Optimization

- List of Root Causes

Testing of Trustworthy Systems

#UCAAT
Proposed Framework (Optimization)

**List of Root Causes**

**Optimization**

**STEPS**
- Reduce search space to the identified Root Causes
- Explore a new range of values for user hyperparameter grid
- Perform N iterations and return the best hyperparameter values
Future Works

- Investigate efficient ways of selecting a new range of hyperparameter values
- Evaluate the performance of our framework against existing approaches
- Extend our framework to include data debugging using causal reasoning
Conclusion

- We argued that debugging should be performed before optimization.

- Our framework can help in:
  - Identifying the root cause of a hyperparameter misconfiguration.
  - Reducing the cost involved in hyperparameter optimization and improve on its result.
  - Making the performance of an ML model interpretable/explainable.
Any questions?

(dapaah@cs-goettingen.de)