Debugging the Machine Learning Pipeline

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joint work with Xuezhou Zhang, Stephen Wright
Interpretable ML Symposium, NIPS 2017
Debugging provides an opportunity for machine learning interpretability.
Harry Potter toy example
Hired by the Ministry of Magic?

- yes
- no

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![Scatter plot with X-axis: magical heritage, Y-axis: education. Points represent data points with a higher concentration at the lower end of the magical heritage axis and the middle range of the education axis.](image-url)
Data contain historical biases

Learned vs. ideal decision boundary

(RBF kernel logistic regression)
Trusted items

- obtained by expensive vetting
- insufficient to learn from
Debugging using trusted items

- propose training label bugs
- flipping them makes re-trained model agree with trusted items
Proposed bugs

- given to experts to interpret

![Graph showing magical heritage vs education](image-url)
The ML pipeline

\[
\text{data } (X, Y) \rightarrow \text{learner } \ell \rightarrow \text{parameters } \lambda \rightarrow \text{model } \hat{\theta}
\]

\[
\hat{\theta} = \arg\min_{\theta \in \Theta} \ell(X, Y, \theta) + \lambda \|\theta\|
\]
Postconditions

$$\Psi(\hat{\theta})$$

Examples:

- “The learned model must correctly predict an important item \((\tilde{x}, \tilde{y})\)”

  $$\hat{\theta}(\tilde{x}) = \tilde{y}$$

- “The learned model must satisfy individual fairness”

  $$\forall x, x', |p(y = 1 \mid x, \hat{\theta}) - p(y = 1 \mid x', \hat{\theta})| \leq L\|x - x'\|$$
Bug Assumptions

- $\Psi$ satisfied if we were to train through "clean pipeline"
- bugs are changes to the clean pipeline
- $\Psi$ violated on the dirty pipeline
This is not our goal

Just to learn a better model:

$$\min_{\theta \in \Theta} \ell(X, Y, \theta) + \lambda \|\theta\|$$

s.t. \(\Psi(\theta) = \text{true}\)
This is our goal

To identify bugs and fix them (and learn a better model):

\[
\min_{Y', \hat{\theta}} \|Y - Y'\|
\]

s.t. \( \Psi(\hat{\theta}) = \text{true} \)

\[\hat{\theta} = \arg\min_{\theta \in \Theta} \ell(X, Y', \theta) + \lambda\|\theta\|\]
Special case: bugs in training labels

- $\Psi$ satisfied if we were to train on “clean data” $(X, Y')$
- bugs are changes to clean labels

$$(X, Y) = (X, Y' + \Delta)$$

- not just about outliers
- may contain systematic biases
Input / output to our debugger

Input:
1. dirty training set \((X, Y)\)
2. trusted items \((\tilde{X}, \tilde{Y})\)
3. the learner

Output:
1. \(Y'\)
2. confidence
Formulation equivalent to machine teaching

\[
\begin{align*}
\min_{Y'} & \quad \|Y' - Y\| \\
\text{s.t.} & \quad \hat{\theta}(\tilde{X}) = \tilde{Y} \\
\hat{\theta} & = \arg\min_{\theta \in \Theta} \frac{1}{n} \sum_{i=1}^{n} \ell(x_i, y_i', \theta) + \lambda \|\theta\|^2
\end{align*}
\]

Difficult!

- combinatorial
- bilevel optimization (Stackelberg game)

[Dec. 9 Workshop on Teaching Machines, Robots, and Humans]
Combinatorial to continuous relaxation

step 1. label to probability simplex

\[ y'_i \rightarrow \delta_i \in \Delta \]

step 2. counting to probability mass

\[ \|Y' - Y\| \rightarrow \frac{1}{n} \sum_{i=1}^{n} (1 - \delta_{i,y_i}) \]

step 3. soften postcondition

\[ \hat{\theta}(\tilde{X}) = \tilde{Y} \rightarrow \frac{1}{m} \sum_{i=1}^{m} \ell(\tilde{x}_i, \tilde{y}_i, \theta) \]
Continuous now, but still bilevel

\[
\begin{align*}
\argmin_{\delta \in \Delta^n, \hat{\theta}} & \quad \frac{1}{m} \sum_{i=1}^{m} \ell(\tilde{x}_i, \tilde{y}_i, \hat{\theta}) + \gamma \frac{1}{n} \sum_{i=1}^{n} (1 - \delta_{i,y_i}) \\
s.t. & \quad \hat{\theta} = \argmin_{\theta} \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{k} \delta_{ij} \ell(x_i, j, \theta) + \lambda \|\theta\|^2
\end{align*}
\]
Removing the lower level problem

\[ \hat{\theta} = \text{argmin}_{\theta} \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{k} \delta_{ij} \ell(x_i, j, \theta) + \lambda \|\theta\|^2 \]

step 1. the KKT condition

\[ \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{k} \delta_{ij} \nabla_{\theta} \ell(x_i, j, \theta) + 2\lambda \theta = 0 \]

step 2. plug implicit function \( \theta(\delta) \) into upper level problem

\[ \text{argmin}_{\delta} \frac{1}{m} \sum_{i=1}^{m} \ell(\tilde{x}_i, \tilde{y}_i, \theta(\delta)) + \gamma \frac{1}{n} \sum_{i=1}^{n} (1 - \delta_{i,y_i}) \]

step 3. compute gradient \( \nabla_{\delta} \) with implicit function theorem
Software available.
Harry Potter Toy Example

data

our debugger

influence function

nearest neighbor

label noise detection

average PR
Another special case: bug in regularization weight

(logistic regression)
Postcondition violated

\( \Psi(\hat{\theta}) \): Individual fairness (Lipschitz condition)

\[ \forall x, x', |p(y = 1 \mid x, \hat{\theta}) - p(y = 1 \mid x', \hat{\theta})| \leq L \|x - x'\| \]
Bug assumption

Learner’s regularization weight $\lambda = 0.001$ was inappropriate

$$\hat{\theta} = \arg\min_{\theta \in \Theta} \ell(X, Y, \theta) + \lambda \|\theta\|^2$$
Debugging formulation

\[
\begin{align*}
\min_{\lambda', \hat{\theta}} & \quad (\lambda' - \lambda)^2 \\
\text{s.t.} & \quad \Psi(\hat{\theta}) = \text{true} \\
& \quad \hat{\theta} = \arg\min_{\theta \in \Theta} \ell(X, Y, \theta) + \lambda' \|\theta\|^2
\end{align*}
\]
Suggested bug

\[ \lambda = 0.001 \rightarrow \lambda' = 121 \]
Call for ML bug repository

- like software bug repositories in software engineering
- need data provenance
  - which training items (or other things) were wrong
  - what they should be
References

- Xuezhou Zhang, Xiaojin Zhu, and Stephen Wright. Training set debugging using trusted items. AAAI 2018
- Shalini Ghosh, Patrick Lincoln, Ashish Tiwari, and Xiaojin Zhu. Trusted machine learning for probabilistic models. –
  
  http://www.cs.wisc.edu/~jerryzhu/machineteaching/