Data Shapley: Equitable Valuation of Data for Machine Learning

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Citation

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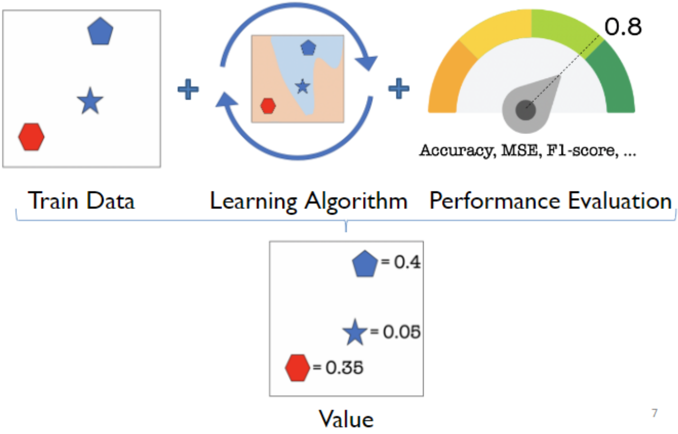
Contents

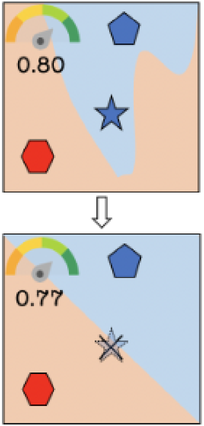
Data Valuation and ML



Leave One Out Method

$$LOO\ for\ point\ i = Performance(D) - Performance(D - \{i\})$$

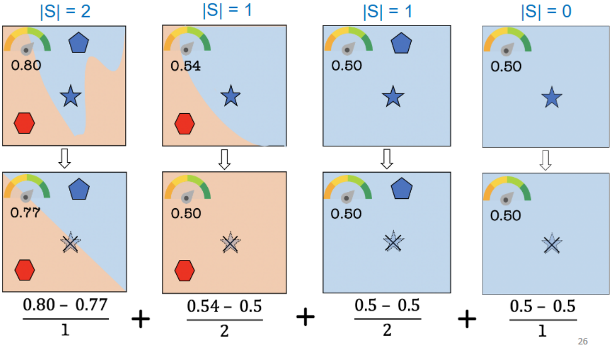
Leave One Out Method



Data Shapley Value

$$SV \text{ for point } i = C \sum_{S \subseteq D - \{i\}} \frac{Performance(S \bigcup \{i\}) - Performance(S)}{\binom{|D|-1}{|S|}}$$

Data Shapley Value



Truncated Monte Carlo

Algorithm 1 **Truncated Monte Carlo Shapley**

Input: Train data $D = \{1, \ldots, n\}$, learning algorithm $\mathcal{A}$, performance score V
Output: Shapley value of training points: $\phi_1, \ldots, \phi_n$

Initialize $\phi_i = 0$ for $i = 1, \ldots, n$ and $t = 0$
while Convergence criteria not met **do**
  $t \leftarrow t + 1$
  π^t: Random permutation of train data points
  $v_0^t \leftarrow V(\emptyset, \mathcal{A})$
  for $j \in \{1, \ldots, n\}$ **do**
    if $|V(D) - v_{j-1}^t| <$ Performance Tolerance **then**
      $v_j^t = v_{j-1}^t$
    else
      $v_j^t \leftarrow V(\{\pi^t[1], \ldots, \pi^t[j]\}, \mathcal{A})$
    end if
    $\phi_{\pi^t[j]} \leftarrow \frac{t-1}{t}\phi_{\pi^{t-1}[j]} + \frac{1}{t}(v_j^t - v_{j-1}^t)$
  end for
end for

Truncation

- V (S) performance on a test set after being trained on S
- as S increases, change in performance by adding only one point decreases
- Truncate based on the marginal contribution within V

Example

Assume 4 data points: A,B,C,D

- Sample a permutation of data points say B, C, A, D
- scan from left to right in one such sample of permutation B$-$ $>$ C$-$ $>$ A$-$ $>$ D
- Marginal Contribution for each sample At Step 3, V (B, C, A) $-$ V (B, C), will be less than V (B, C) $-$ V (B) At step 2
- Truncate at a predefined tolerance: Only do B$-$ $>$ C$-$ $>$ A and assign zero as marginal contribution to the rest

Gradient Based Approximation

Algorithm 2 Gradient Shapley

Input: Parametrized and differentiable loss function $\mathscr{L}(.;\theta)$, train data $D = \{1, \ldots, n\}$, performance score function $V(\theta)$

Output: Shapley value of training points: $\phi_1, \ldots, \phi_n$

Initialize $\phi_i = 0$ for $i = 1, \ldots, n$ and $t = 0$

while Convergence criteria not met **do**

  $t \leftarrow t + 1$

  π^t: Random permutation of train data points

  $\theta_0^t \leftarrow$ Random parameters

  $v_0^t \leftarrow V(\theta_0^t)$

  for $j \in \{1, \ldots, n\}$ **do**

    $\theta_j^t \leftarrow \theta_{j-1}^t - \alpha \nabla_\theta \mathscr{L}(\pi^t[j]; \theta_{j-1})$

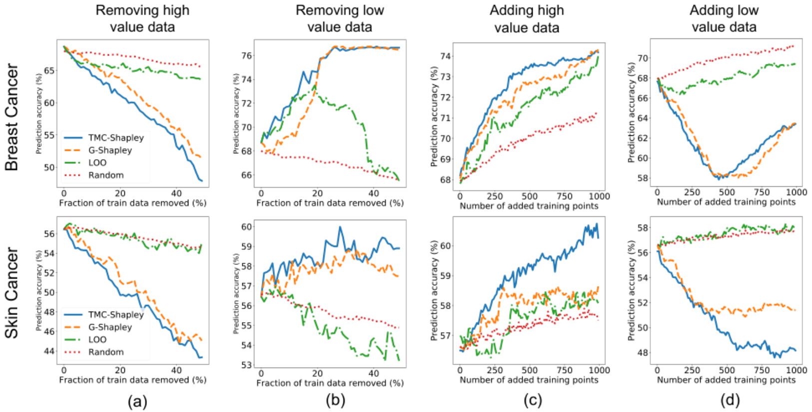
    $v_j^t \leftarrow V(\theta_j^t)$

    $\phi_{\pi^t[j]} \leftarrow \frac{t-1}{t} \phi_{\pi^{t-1}[j]} + \frac{1}{t}(v_j^t - v_{j-1}^t)$

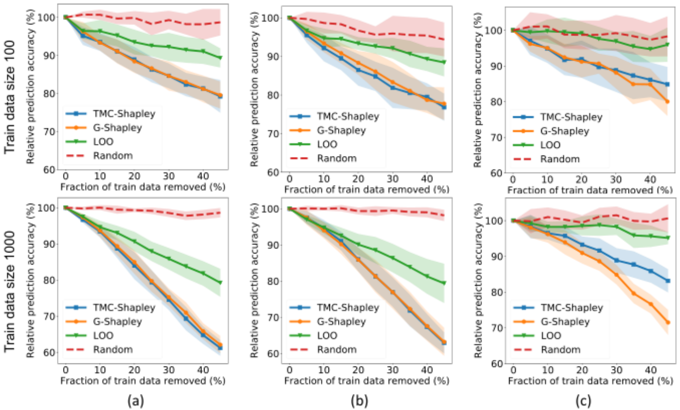
  end for

end for

Experiment Result



Synthesis Data



Mislabeled Data

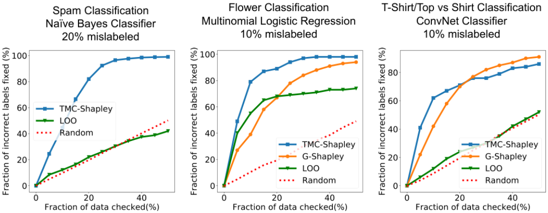


Figure 3. **Correcting Flipped Labels** We inspect train data points from the least valuable to the most valuable and fix the mislabeled examples. As it is shown, Shapley value methods result in the earliest detection of mislabeled examples. While leave-one-out works reasonably well on the Logistic Regression model, it's performance on the two other models is similar to random inspection.

Noisy Image and Group Data

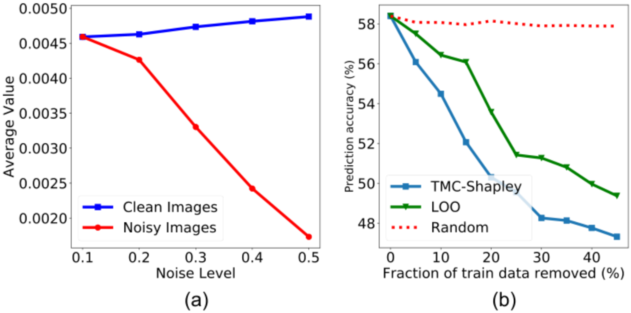


Figure 5. (a) **Value and data quality**: White noise is added to 10% of training points. As the noise level increases, the average TMC-Shapley value of noisy images becomes decreases compared to that of clean images. (b) **Group Shapley:** Removing the valuable groups degrades the performance more than removing groups with the highest leave-one-out score.

Conclusion

- Introduces a fair data pricing approach based on Shapley values to quantify the contribution of each data point to machine learning models.
- the value of individual datum depends on the learning algorithm, evaluation metric as well as other data points in the training set
- Demonstrates the effectiveness of this approach across various tasks and models

Thoughts

- Explore combining Shapley value estimation with different optimization algorithms to achieve faster convergence rates.
- Assuming Shapley values are sparse, investigate the potential of using compressed sensing techniques to reconstruct true Shapley values with fewer samples.

Thanks!