Data Shapley: Equitable Valuation of Data for Machine Learning

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Citation

- Ghorbani, A. Zou, J. Data Shapley: Equitable Valuation of Data for Machine Learning. in International Conference on Machine Learning 2242–2251 (2019).

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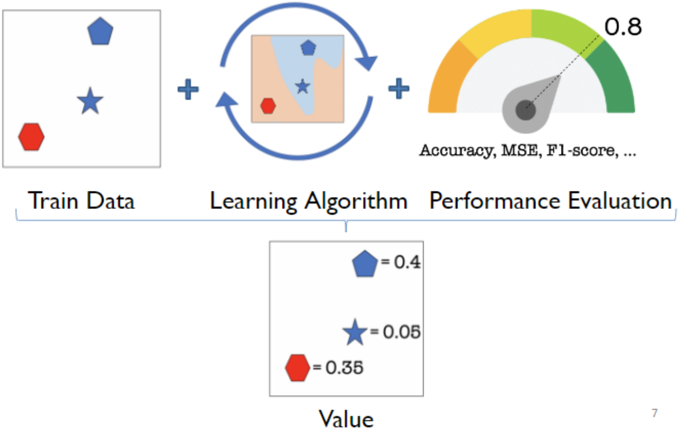
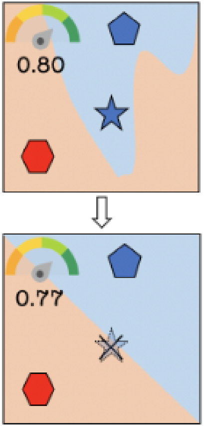


Leave One Out Method

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

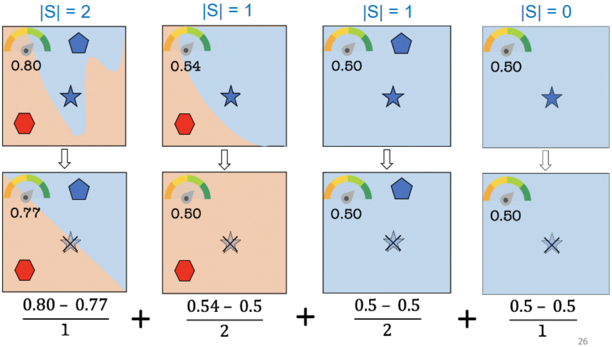
Leave One Out Method



Data Shapley Value

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

Data Shapley Value



Truncated Monte Carlo

Algorithm 1 Truncated Monte Carlo Shapley

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

Initialize $\phi_i = 0$ for $i = 1, \dots, n$ 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 $j \in \{1, \dots, n\}$ **do**
    if $|V(D) - v_{j-1}^t| <$ Performance Tolerance **then**
      $v_j^t = v_{j-1}^t$
    else
      $v_j^t \leftarrow V(\{\pi^t[1], \dots, \pi^t[j]\}, \mathcal{A})$
    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**

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

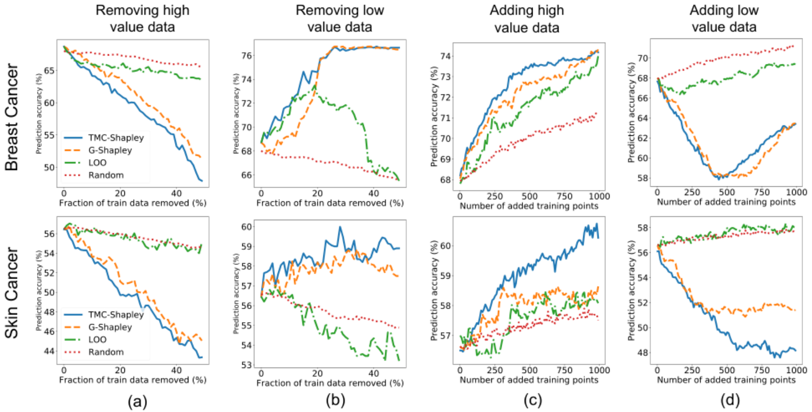
    $v_j^t \leftarrow V(\theta_j^t)$

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

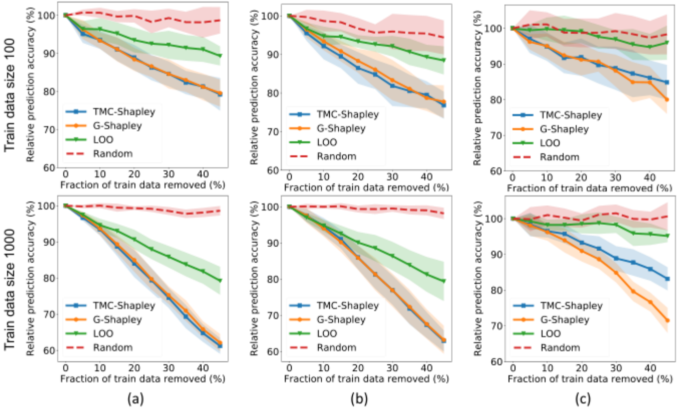
  end for

end for

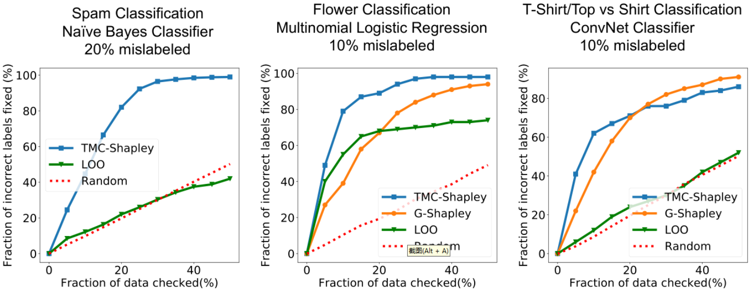
Experiment Result



Synthesis Data



Mislabeled Data



Noisy Image and Group Data

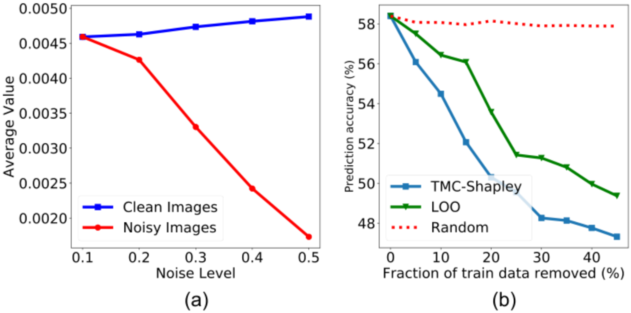


Figure 5. (a) **Value and data quality**: White noise is added to 10% of training points. As the noise level increases, the average TMC-Shapley value of noisy images becomes decreases compared to that of clean images. (b) **Group Shapley:** Removing the valuable groups degrades the performance more than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

Thoughs

- 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!