

Shapley Deep Learning: A Consensus for General-Purpose Vision Systems [Supplementary Materials]

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Optimized Shapley Learning

In this section we sketch the changes that need to be made the Shapely algorithm more efficient for computing the contribution of each model in \mathcal{M} . We use intermediate values $\phi(\cdot, \cdot, \cdot)$ analogous to the values $\beta(\cdot, \cdot)$ that constituted the base of the Banzhaf algorithm. For any vertex $v \in T$, set $G \subseteq U$ and integer $k = 0, \dots, |G|$, let

$$\phi(v, G, k) := \frac{1}{|G|+1} \sum_{\substack{S \subseteq G \\ |S|=k}} \binom{|G|}{k}^{-1} \times P[v, S]. \quad (1)$$

Let us also consider $\phi(v, G)$ as a vector containing all of the values $\phi(v, G, \cdot)$:

$$\phi(v, G) = (\phi(v, G, k))_{k=0}^{|G|}. \quad (2)$$

For the sake of clarity, let us interpret $\phi(v, G, k) = 0$ for $k < 0$ or $k > |G|$. Let $v \in T$, $G \subseteq U$ and $k \in \{0, \dots, |G|\}$. Let $y \in U \setminus G$. we get:

$$\phi(v, G \cup \{y\}, k) = \frac{|G|+1-k}{|G|+2} \times \phi(v, G, k) + \frac{k}{|G|+2} \times \Delta_{v,y} \times \phi(v, G, k-1).$$

proof Let $m = |G| + 1$, we have:

$$\begin{aligned} \phi(v, G \cup \{y\}, k) &= \sum_{\substack{S \subseteq G \cup \{y\} \\ |S|=k}} \frac{1}{m+1} \binom{m}{k}^{-1} P[v, S] \\ &= \left(\sum_{\substack{S \subseteq G \\ |S|=k}} \frac{1}{m+1} \binom{m}{k}^{-1} P[v, S] \right) + \\ &\left(\sum_{\substack{y \in S \subseteq G \cup \{y\} \\ |S|=k}} \frac{1}{m+1} \binom{m}{k}^{-1} P[v, S] \right) \\ &= \left(\sum_{\substack{S \subseteq G \\ |S|=k}} \frac{m-k}{m+1} \cdot \frac{1}{m} \binom{m-1}{k}^{-1} P[v, S] \right) + \end{aligned}$$

$$\begin{aligned} &\left(\sum_{\substack{S \subseteq G \\ |S|=k-1}} \frac{k}{m+1} \cdot \Delta_{v,y} \cdot \frac{1}{m} \binom{m-1}{k-1}^{-1} P[v, S] \right) \\ &= \frac{m-k}{m+1} \cdot \phi(v, G, k) + \frac{k}{m+1} \cdot \Delta_{v,y} \cdot \phi(v, G, k-1). \end{aligned}$$

Shapely value recursive equation designed to demonstrate that the complexity of computing each $\phi(v, F_v)$ is in $O(|F_v|) = O(D)$ time. This overhead is a result of the fact that the vectors $\phi(\cdot, \cdot)$ used have coordinates up to D . Keep in mind that similar values had only one coordinate when computing Banzhaf value explanations, so a similar transition could be conducted in constant time. As a result, the basic algorithm of Lunderg revised the calculation of the vectors $\phi(v, F_v)$ where it tends to take $O(LD^2)$ time. We need to create a Shapley formula to get an asymptotically accelerated $O(LD)$ time algorithm for calculating Shapley interpretations using our approach. Consider the following funding to that end:

$$\Psi(v, k) = \sum_{l \in L_v} f(l) \cdot \phi(l, F_l, k), \quad (3)$$

A bottom-up computation may be employed to calculate all the values $\Psi(v, k)$ for $v \in T$ in $O(LD)$ time by proceeding player similarly.

We also have:

$$\gamma(v, k) = \sum_{l \in L_v} f(l) \cdot \phi(l, F_l \setminus \{d_{p_v}\}, k) \quad (4)$$

and

$$\Gamma(v) := \sum_{l \in L_v} f(l) \cdot \Phi(l, F_l \setminus \{d_{p_v}\}). \quad (5)$$

As a result, we can reformulate Shapely as follows:

$$\begin{aligned}
\phi_i &= \sum_{\substack{l \in L(T) \\ i \in F_l}} f(l) \cdot (\Delta_{l,i} - 1) \cdot \Phi(l, F_l \setminus \{i\}) \\
&= \sum_{\substack{v \in T \\ d_{p_v} = i}} \sum_{l \in L_v} f(l) \cdot (\Delta_{l,i} - 1) \cdot \Phi(l, F_l \setminus \{i\}) \\
&= \sum_{\substack{v \in T \\ d_{p_v} = i}} (\Delta_{v,i} - 1) \sum_{l \in L_v} f(l) \cdot \Phi(l, F_l \setminus \{i\}) \\
&= \sum_{\substack{v \in T \\ d_{p_v} = i}} (\Delta_{v,i} - 1) \cdot \Gamma(v).
\end{aligned}$$

It is worth noting that the preceding derivation provides a $O(L)$ time reduction from computing all ϕ_i to determining all $\Gamma(v)$ values. Once we possess the entire values $\gamma(v, k)$, we can clearly obtain them by addition operation performed in $O(LD)$ time. The following lemma establishes a connection between the values $\Psi(\cdot, \cdot)$ and $\gamma(\cdot, \cdot)$.

lemma. *Let $v \in T$, $v \neq \rho$. Suppose the sets F_l have equal sizes s for all $l \in L_v$. Then, for any $k = 0, \dots, s$, we have:*

$$\Psi(v, k) = \frac{s-k}{s+1} \cdot \gamma(v, k) + \frac{k}{s+1} \cdot \Delta_{v, d_{p_v}} \cdot \gamma(v, k-1).$$

proof. For any $l \in L_v$ we have:

$$\begin{aligned}
\phi(l, F_l, k) &= \frac{|F_l| - k}{|F_l| + 1} \phi(l, F_l \setminus \{d_{p_v}\}, k) - \frac{k}{|F_l| + 1} \cdot \Delta_{l, d_{p_v}} \cdot \phi(l, F_l \setminus \{d_{p_v}\}, k-1) \\
\phi(l, F_l, k) &= \frac{s-k}{s+1} \phi(l, F_l \setminus \{d_{p_v}\}, k) - \frac{k}{s+1} \cdot \Delta_{l, d_{p_v}} \cdot \phi(l, F_l \setminus \{d_{p_v}\}, k-1).
\end{aligned}$$

We get the preferred equality by adding the above to all $l \in L_v$ and then using the following equality:

$$\Delta_{l, d_{p_v}} = \Delta_{v, d_{p_v}}$$