

Tuesday, May 5

Last class!

• "Quiz" for specific feedback

↳ topics

↳ course components
(readings, activities, reviews,
self-grades, whiteboard lectures)

Student experience surveys

for more general feedback

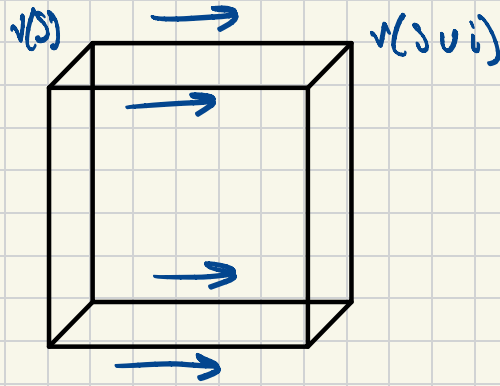
Senior projects / talks due Thursday midnight

Presentations Thursday, May 14 2-5pm

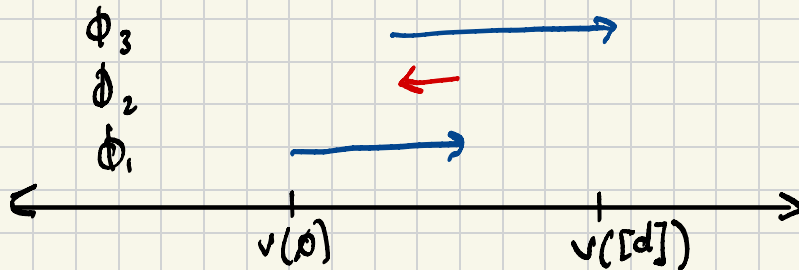
Shapley Value

$$\phi_i = \sum_{S \subseteq [d] \setminus \{i\}} [v(S \cup i) - v(S)] \mu_S$$

where $\mu_S = \frac{1}{d \binom{d-1}{|S|}}$



Efficiency: $\sum_{i=1}^d \phi_i = v([d]) - v(\emptyset)$



Monte Carlo Estimator

Sample m sets S w.p. P_S

$$\tilde{\phi}_i^{MC} = \frac{1}{m} \sum_{j=1}^m [v(S_j; u_i) - v(S_j)] \frac{\mu_S}{P_S} \stackrel{\text{choose } \mu_S = P_S}{=} \frac{1}{m} \sum_{j=1}^m v(S_j; u_i) - v(S_j)$$

$$\mathbb{E}[\tilde{\phi}_i^{MC}] = \phi_i$$

$$\text{Var}(\tilde{\phi}_i^{MC}) = \frac{1}{m} \sum_{S \subseteq [d], \{i\}} (v(S; u_i) - v(S))^2 \mu_S$$

Idea: Instead of using $v(S; u_i)$, $v(S)$ only for i ,
let's reuse for all $\tilde{\phi}_j$

Maximum Sample Reuse

$$\phi_i = \sum_{S \subseteq [d], i \in S} [v(S_{\setminus i}) - v(S)] \mu_S$$

← rewrite so $v(S)$ appears by itself in each term

=

=

$$\tilde{\phi}_i^{MSR} =$$

$\text{Var}(\tilde{\phi}_i^{MSR})$ depends on ...

Linear Regression Perspective

$$\boxed{v(\phi) = 0 \quad \text{wLOG}}$$

$$\phi = \begin{bmatrix} \phi_1 \\ \phi_2 \\ \vdots \\ \phi_d \end{bmatrix} = \arg \min_{\beta \in \mathbb{R}^d: \langle \beta, \mathbf{1} \rangle = v([d])} \sum_{S: 0 < |S| < d} w_S (v(S) - \sum_{i \in S} \beta_i)^2$$

← ensure efficiency

where $w_S = \frac{1}{\binom{d}{|S|} |S| (d-|S|)}$

$$A' \in \mathbb{R}^{2^d-2 \times d}, \quad b' \in \mathbb{R}^{2^d-2}$$

For $\emptyset \subset S \subset [d]$,

$$[A']_{s,i} = \mathbb{1}[i \in S] \sqrt{w_S}, \quad [b']_s = v(S) \sqrt{w_S}$$

$$\phi = \arg \min_{\beta \in \mathbb{R}^d: \langle \beta, \mathbf{1} \rangle = v([d])} \|A'\beta - b'\|_2^2$$

← weird form...

$$\phi = \operatorname{argmin}_{\beta \in \mathbb{R}^d: \langle \beta, \mathbf{1} \rangle = v(d)} \|A'\beta - b'\|_2^2 \quad \left\langle \mathbf{1}, \mathbf{1} \frac{v(d)}{d} \right\rangle = v(d)$$

$$= \operatorname{argmin}_{\beta_{\perp} \in \mathbb{R}^d: \langle \beta_{\perp}, \mathbf{1} \rangle = 0} \|A'(\beta_{\perp} + \mathbf{1} \frac{v(d)}{d}) - b'\|_2^2 + \frac{\mathbf{1} v(d)}{d}$$

$$= \operatorname{argmin}_{\beta \in \mathbb{R}^d} \| \underbrace{A'P}_{A} \beta + \underbrace{A'\mathbf{1} \frac{v(d)}{d}}_{-b} - b' \|_2^2 + \mathbf{1} \frac{v(d)}{d}$$

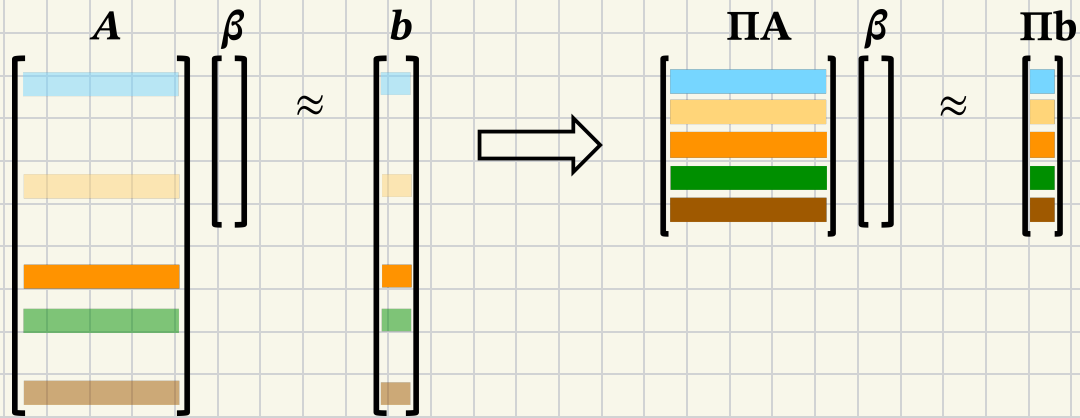
where $P = I - \frac{1}{d} \mathbf{1}\mathbf{1}^T$ so $\langle \mathbf{1}, P\beta \rangle = \mathbf{1}^T P\beta$

$$= \mathbf{1}^T (\beta - \frac{1}{d} \mathbf{1}\mathbf{1}^T \beta)$$

$$= \mathbf{1}^T \beta - \frac{d}{d} \mathbf{1}^T \beta = 0$$

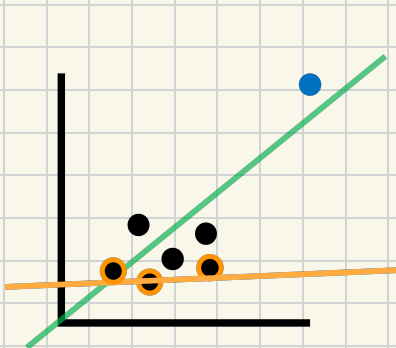
$$= \operatorname{argmin}_{\beta \in \mathbb{R}^d} \|A\beta - b\|_2^2 + \mathbf{1} \frac{v(d)}{d}$$

Leverage Score Sampling

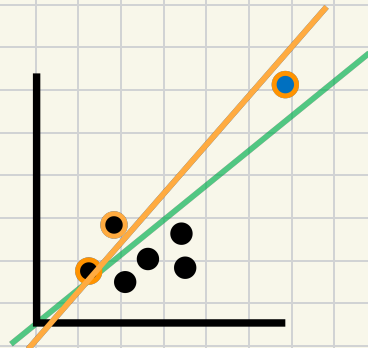


$$l_s = A_s^T (A^T A)^{\dagger} A_s$$

$$= \frac{1}{d(d-1)} \frac{1}{|s|}$$



VS.



Regression Adjustment

1. Fit surrogate $\tilde{v} \approx v$

2. Return $\phi_i(\tilde{v}) + \tilde{\phi}_i(v - \tilde{v})$

Exercise: $\phi_i(v) = \phi_i(\tilde{v}) + \phi_i(v - \tilde{v})$

Use linear function, polynomial function, trees, Gaussian Processes
where surrogate is expressive, and we can efficiently
extract its Shapley values