

Randomized Computation of Active Subspaces

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Motivation

Given: Differentiable function $f : \mathbb{R}^m \rightarrow \mathbb{R}$ where m large

Want: Influential parameters of f

- 1 Detect **active subspace** $\mathcal{S} \subset \mathbb{R}^m$ where f **most sensitive** to change (varies strongly)
- 2 Approximate f by response surface over \mathcal{S}

Existing Work:

Active subspaces [Russi 2010]

Stochastic PDEs [Constantine et al. 2012, 2014], [Stoyanov et al. 2014]

Reduced-order nonlinear models [Bang et al. 2012]

Airfoil design and manufacturing [Namura et al. 2015], [Chen et al. 2011]

Combustion [Bauernheim et al. 2014], [Constantine et al. 2011]

Solar cells [Constantine et al. 2014]

Idea

Given: Function $f : \mathbb{R}^m \rightarrow \mathbb{R}$

- 1 From $\nabla f(x)$ construct "sensitivity" matrix $E \in \mathbb{R}^{m \times m}$
- 2 Dominant eigenvectors of $E \Rightarrow$ active subspace \mathcal{S}

Problem: Elements of E too expensive to compute
(high-dimensional integrals)

- 4 Approximate E by Monte Carlo: $\hat{E} \in \mathbb{R}^{m \times m}$
- 5 Dominant eigenvectors of $\hat{E} \Rightarrow$ approximate subspace $\hat{\mathcal{S}}$

Our contribution: Probabilistic bound for $\sin \angle(\mathcal{S}, \hat{\mathcal{S}})$

Tight if: E has low numerical rank and large eigenvalue gap

Overview

① Assumptions

- "Sensitivity" matrix E
- Active subspace \mathcal{S}
- Monte Carlo approximation \hat{E}
- Approximate subspace $\hat{\mathcal{S}}$

② Accuracy of $\hat{\mathcal{S}}$

- Structural (deterministic) bound for subspace angle
- Matrix concentration inequality
- Probabilistic bound for number of Monte Carlo samples

Assumptions

The function is somewhat nice

- $f : \mathbb{R}^m \rightarrow \mathbb{R}$ continuously differentiable
- Lipschitz constant $\|\nabla f(x)\| \leq L$ (2 norm)

Monte Carlo sampling

- Random vectors $\mathbf{X} \in \mathbb{R}^m$ with probability density $\rho(x)$
- Expected value of function h with respect to \mathbf{X}

$$\mathbb{E}[h(\mathbf{X})] \equiv \int_{\mathbb{R}^m} h(x) \rho(x) dx$$

"Sensitivity" Matrix E

Informative directional derivatives

$$E \equiv \int_{\mathbb{R}^m} \nabla f(x)(\nabla f(x))^T \rho(x) dx$$

- $E \in \mathbb{R}^{m \times m}$ symmetric positive semi-definite
- Eigenvalue decomposition $E = V \Lambda V^T$
- Eigenvectors $V = (v_1 \ \dots \ v_m)$
 v_j is **direction of sensitivity** of f
- Eigenvalues $\Lambda = \text{diag}(\lambda_1 \ \dots \ \lambda_m)$
 $\lambda_j = \mathbb{E} \left[(v_j^T \nabla f(\mathbf{X}))^2 \right]$ **average sensitivity** along v_j

Active Subspace \mathcal{S}

Dominant eigenvalues of $E = V\Lambda V^T$

$$\Lambda = \text{diag}(\lambda_1 \ \cdots \ \lambda_k \ \lambda_{k+1} \ \cdots \ \lambda_m)$$

- Large eigenvalue gap

$$\lambda_1 \geq \cdots \geq \lambda_k \gg \lambda_{k+1} \geq \cdots \geq \lambda_m$$

- k dominant eigenvalues λ_j : **Indicators** of high sensitivity
- k dominant eigenvectors v_j : **Directions** of high sensitivity

Orthonormal basis for active subspace

$$\mathcal{S} \equiv \text{range}(v_1 \ \cdots \ v_k)$$

Monte Carlo Approximation \hat{E}

- Sample $n \ll m$ training points $x_j \in \mathbb{R}^m$ according to $\rho(x)$

$$\hat{E} = \frac{1}{n} \sum_{j=1}^n \nabla f(x_j) (\nabla f(x_j))^T$$

- Eigenvalue decomposition $\hat{E} = \hat{V} \hat{\Lambda} \hat{V}^T$

$$\hat{\Lambda} = \text{diag} \left(\hat{\lambda}_1 \quad \cdots \quad \hat{\lambda}_k \quad \hat{\lambda}_{k+1} \quad \cdots \quad \hat{\lambda}_m \right)$$

- Assume: Eigenvalue gap in **same** location as for E

$$\hat{\lambda}_1 \geq \cdots \geq \hat{\lambda}_k \gg \hat{\lambda}_{k+1} \geq \cdots \geq \hat{\lambda}_m$$

Orthonormal basis for approximate subspace

$$\hat{\mathcal{S}} \equiv \text{range} \left(\hat{v}_1 \quad \cdots \quad \hat{v}_k \right)$$

Accuracy of Approximate Subspace

Approach

- 1 Structural (deterministic) bound

Bound $\sin \angle(\mathcal{S}, \hat{\mathcal{S}})$ in terms of $\|\hat{E} - E\|$

- 2 Probabilistic bound

Bound $\|\hat{E} - E\|$ in terms of sampling amount n

- 3 Combine the two bounds

Sampling amount n so that $\sin \angle(\mathcal{S}, \hat{\mathcal{S}}) \leq \epsilon$

Structural Bound: Subspace Perturbation

based on [Stewart 1973]

- Eigenvalues of E : $\lambda_1 \geq \dots \geq \lambda_k > \lambda_{k+1} \geq \dots \geq \lambda_m$
- Active subspace: $\mathcal{S} = \text{range}(v_1 \ \dots \ v_k)$
- Approximate subspace: $\hat{\mathcal{S}} = \text{range}(\hat{v}_1 \ \dots \ \hat{v}_k)$
- Small enough perturbation: $\|\hat{E} - E\| \leq \frac{1}{4}(\lambda_k - \lambda_{k+1})$

Then

$$\sin \angle(\mathcal{S}, \hat{\mathcal{S}}) \leq 4 \frac{\|\hat{E} - E\|}{\lambda_k - \lambda_{k+1}}$$

If $\lambda_{k+1} - \lambda_k \gg 0$ then active subspace \mathcal{S} well-conditioned

Probabilistic Bound: Matrix Perturbation

- **Want:** Probabilistic bound for $\|\hat{E} - E\|$
- **Exact:** $E = \int_{\mathbb{R}^m} \nabla f(x) (\nabla f(x))^T \rho(x) dx$
- **Monte Carlo approximation:** $\hat{E} = \frac{1}{n} \sum_{j=1}^n \nabla f(x_j) (\nabla f(x_j))^T$
- **Idea:** \hat{E} is average of **matrix-valued random variables**

$$\nabla f(x_j) (\nabla f(x_j))^T$$

with mean $\mathbb{E} [\nabla f(x_j) (\nabla f(x_j))^T] = E$

Next: **Matrix concentration** for $\hat{E} - E$

Matrix Bernstein Concentration [Minsker 2011, Tropp 2015]

Given

- Independent random symmetric matrices X_j , $1 \leq j \leq n$
- Norm: $\max_{1 \leq j \leq n} \|X_j\| \leq \beta$
- Zero mean: $\mathbb{E}[X_j] = 0$, $1 \leq j \leq n$
- Matrix variance: $\sum_{j=1}^n \mathbb{E}[X_j^2] \preceq P$ for some P
- Tolerance: $\epsilon \geq \|P\|^{1/2} + \beta$

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Probability that the sum is "large"

$$\mathbb{P} \left[\left\| \sum_{j=1}^n X_j \right\| \geq \epsilon \right] \leq 4 \frac{\text{trace}(P)}{\|P\|} \exp \left(\frac{-\epsilon^2/2}{\|P\| + \beta\epsilon/3} \right)$$

Interpretation of Matrix Concentration

$$\mathbb{P} \left[\left\| \sum_{j=1}^n X_j \right\| \geq \epsilon \right] \leq 4 \frac{\text{trace}(P)}{\|P\|} \exp \left(\frac{-\epsilon^2/2}{\|P\| + \beta\epsilon/3} \right)$$

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- Sum = Deviation from the mean

$$\sum_{j=1}^n X_j = \sum_{j=1}^n X_j - \underbrace{\mathbb{E} \left[\sum_{j=1}^n X_j \right]}_{=0}$$

- Variance: Numerical rank* of P = Stable rank of $P^{1/2}$

$$\frac{\text{trace}(P)}{\|P\|_2} = \left(\frac{\|P^{1/2}\|_F}{\|P^{1/2}\|_2} \right)^2$$

* Intrinsic dimension, effective rank

Applying the Matrix Concentration

Check the assumptions for $\hat{E} - E = \sum_{j=1}^n X_j$

- Independent random: $X_j \equiv \frac{1}{n} (\nabla f(x_j) (\nabla f(x_j))^T - E)$
- Zero mean: $\mathbb{E}[X_j] = 0$
- Bounded norm: $\|X_j\| \leq L^2/n$
- Variance: $\mathbb{E}[X_j^2] = \frac{1}{n^2} \left[\int (\nabla f(x) (\nabla f(x))^T)^2 \rho(x) dx - E^2 \right]$
- Bound for variance: $P = \frac{L^2}{n} E$

$$\int (\nabla f(x) (\nabla f(x))^T)^2 \rho(x) dx = \underbrace{\|\nabla f(x)\|^2}_{L^2} \underbrace{\int \nabla f(x) (\nabla f(x))^T \rho(x) dx}_E$$

Applying the Matrix Concentration

Absolute error:

$$\mathbb{P} \left[\|\hat{E} - E\| \geq \hat{\epsilon} \right] \leq 4 \frac{\text{trace}(E)}{\|E\|} \exp \left(-\frac{n}{L^2} \frac{\hat{\epsilon}^2/2}{\|E\| + \hat{\epsilon}/3} \right)$$

No explicit dependence on problem dimension m

Error small, if E has low numerical rank

Applying the Matrix Concentration

Absolute error:

$$\mathbb{P} \left[\|\hat{E} - E\| \geq \hat{\epsilon} \right] \leq 4 \frac{\text{trace}(E)}{\|E\|} \exp \left(-\frac{n}{L^2} \frac{\hat{\epsilon}^2/2}{\|E\| + \hat{\epsilon}/3} \right)$$

No explicit dependence on problem dimension m

Error small, if E has low numerical rank

Relative error: Set $\hat{\epsilon} = \|E\| \epsilon$

$$\mathbb{P} \left[\frac{\|\hat{E} - E\|}{\|E\|} \geq \epsilon \right] \leq 4 \frac{\text{trace}(E)}{\|E\|} \exp \left(-n \frac{\|E\|}{L^2} \frac{\epsilon^2/2}{1 + \epsilon/3} \right)$$

Failure Probability

Given $0 < \epsilon < 1$

$$\mathbb{P} \left[\frac{\|\hat{E} - E\|}{\|E\|} \geq \epsilon \right] \leq 4 \underbrace{\frac{\text{trace}(E)}{\|E\|}}_{\text{numerical rank of } E} \exp \left(-n \frac{\|E\|}{L^2} \frac{\epsilon^2/2}{1 + \epsilon/3} \right)$$

The probability is high that \hat{E} has relative error ϵ , if

- Function f is smooth: $L^2/\|E\| \approx 1$
- E has low numerical rank: $\text{trace}(E)/\|E\| \ll m$

Relative Error for Monte Carlo Approximation

For any $\delta > 0$, with probability at least $1 - \delta$

$$\frac{\|\hat{E} - E\|}{\|E\|} \leq \gamma + \sqrt{\gamma(\gamma + 6)}$$

where

$$\gamma \equiv \frac{1}{3n} \frac{L^2}{\|E\|} \ln \left(\frac{4}{\delta} \frac{\text{trace}(E)}{\|E\|} \right)$$

With probability $1 - \delta$, approximation \hat{E} is accurate, if

- Function f is smooth: $L^2/\|E\| \approx 1$
- E has low numerical rank: $\text{trace}(E)/\|E\| \ll m$

Number of Monte Carlo Samples

For any $\delta > 0$, with probability at least $1 - \delta$

$$\frac{\|\hat{E} - E\|}{\|E\|} \leq \epsilon$$

if number of Monte Carlo samples is

$$n \geq \frac{3}{\epsilon^2} \frac{L^2}{\|E\|} \ln \left(\frac{4}{\delta} \frac{\text{trace}(E)}{\|E\|} \right)$$

With probability $1 - \delta$, only few samples to compute \hat{E} , if

- Function f is smooth: $L^2/\|E\| \approx 1$
- E has low numerical rank: $\text{trace}(E)/\|E\| \ll m$

Final bound: Deterministic + Probabilistic

Assumptions

- Lipschitz constant: $\|\nabla f(x)\| \leq L$
- Eigenvalues of E :

$$\underbrace{\lambda_1 \geq \dots \geq \lambda_k}_{\text{Active subspace } \mathcal{S}} \quad \gg \quad \lambda_{k+1} \geq \dots \geq \lambda_m \geq 0$$

$\text{gap} = \frac{\lambda_k - \lambda_{k+1}}{\lambda_1}$

- Numerical rank: $\text{nr}(E) = (\lambda_1 + \dots + \lambda_m)/\lambda_1$
- User-specified error tolerance: $0 < \epsilon < \text{gap}/4$
- User-specified failure probability: $0 < \delta < 1$

Number of Monte Carlo Samples for Subspace Approximation

With probability at least $1 - \delta$

$$\sin \angle(\mathcal{S}, \hat{\mathcal{S}}) \leq 4\epsilon/\text{gap}$$

if number of samples for approximating E is

$$n \geq \frac{3}{\epsilon^2} \frac{L^2}{\|E\|} \ln \left(\frac{4}{\delta} \text{nr}(E) \right)$$

With high probability, only few samples for accurate subspace $\hat{\mathcal{S}}$, if

- Function f is smooth: $L^2/\|E\| \approx 1$
- E has low numerical rank: $\text{nr}(E) \ll m$
- Subspace \mathcal{S} is well-conditioned: $\text{gap} \gg 1$

Summary

Want: Active subspace \mathcal{S} of function $f : \mathbb{R}^m \rightarrow \mathbb{R}$

Dominant eigenspace of "sensitivity" matrix $E \in \mathbb{R}^{m \times m}$

Compute: Subspace $\hat{\mathcal{S}}$ from Monte Carlo approximation of E

Contribution: Probabilistic bounds for $\sin \angle(\mathcal{S}, \hat{\mathcal{S}})$

- **No explicit dependence** on problem dimension m
- **Number of samples** to achieve user-specified error at user-specified probability
- Monte Carlo efficient if
 - E has low numerical rank
 - Subspace \mathcal{S} well-conditioned (large eigenvalue gap)
- **Application:** Construction of response surfaces
 - System of elliptic PDEs, coefficients are log-Gaussian random fields
 - Sensitivity matrix E has dimension $m = 3,495$
 - Active subspace \mathcal{S} has dimension $k = 10$
 - Response surface accurate to 1-2 digits