## **Optimization in Machine Learning**

# Mathematical Concepts Taylor Approximation





#### Learning goals

- Taylor's theorem (univariate)
- Taylor series (univariate)
- Taylor's theorem (multivariate)
- Taylor series (multivariate)

### TAYLOR APPROXIMATIONS

- Mathematically fascinating: Globally approximate function by sum of polynomials determined by local properties
- Extremely important for analyzing optimization algorithms
- Geometry of linear and quadratic functions very well understood
  - $\implies$  use them for approximations







### TAYLOR'S THEOREM (UNIVARIATE)

**Taylor's theorem:** Let  $I \subseteq \mathbb{R}$  be an open interval and  $f \in C^k(I, \mathbb{R})$ . For each  $a, x \in I$ , it holds that

$$f(x) = \underbrace{\sum_{j=0}^{k} \frac{f^{(j)}(a)}{j!} (x-a)^{j}}_{T_{k}(x,a)} + R_{k}(x,a)$$

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with the *k*-th **Taylor polynomial**  $T_k$  and a **remainder term** 

$$R_k(x,a) = o(|x-a|^k)$$
 as  $x \to a$ .

- There are explicit formulas for the remainder
- Wording: We "expand f via Taylor around a"

### **TAYLOR SERIES (UNIVARIATE)**

• If  $f \in C^{\infty}$ , it *might* be expandable around  $a \in I$  as a **Taylor series** 

$$\sum_{k=0}^{\infty} \frac{f^{(k)}(a)}{k!} (x-a)^k$$

- If Taylor series converges to *f* in an interval *I*<sub>0</sub> ⊆ *I* centered at *a* (does not have to), we call *f* an *analytic function*
- Convergence if  $R_k(x,a) 
  ightarrow 0$  as  $k 
  ightarrow \infty$  for all  $x \in I_0$
- Then, for all  $x \in I_0$ :

$$f(x) = \sum_{j=0}^{\infty} \frac{f^{(j)}(a)}{j!} (x-a)^j$$



#### **TAYLOR'S THEOREM (MULTIVARIATE) Taylor's theorem (1st order)**: For $f \in C^1$ , it holds that

$$f(\mathbf{x}) = \underbrace{f(\mathbf{a}) + \nabla f(\mathbf{a})^T(\mathbf{x} - \mathbf{a})}_{T_1(\mathbf{x}, \mathbf{a})} + R_1(\mathbf{x}, \mathbf{a}).$$

**Example:** 
$$f(\mathbf{x}) = \sin(2x_1) + \cos(x_2), \ \mathbf{a} = (1, 1)^T$$
. Since  $\nabla f(\mathbf{x}) = \begin{pmatrix} 2\cos(2x_1) \\ -\sin(x_2) \end{pmatrix}$ ,  
 $f(\mathbf{x}) = T_1(\mathbf{x}) + R_1(\mathbf{x}, \mathbf{a}) = f(\mathbf{a}) + \nabla f(\mathbf{a})^T(\mathbf{x} - \mathbf{a}) + R_1(\mathbf{x}, \mathbf{a})$   
 $= \sin(2) + \cos(1) + (2\cos(2), -\sin(1))^T \begin{pmatrix} x_1 - 1 \\ x_2 - 1 \end{pmatrix} + R_1(\mathbf{x}, \mathbf{a})$ 



× 0 0 × × × **TAYLOR'S THEOREM (MULTIVARIATE)** / 2 **Taylor's theorem (2nd order)**: If  $f \in C^2$ , it holds that

$$f(\mathbf{x}) = \underbrace{f(\mathbf{a}) + \nabla f(\mathbf{a})^T (\mathbf{x} - \mathbf{a}) + \frac{1}{2} (\mathbf{x} - \mathbf{a})^T H(\mathbf{a}) (\mathbf{x} - \mathbf{a})}_{T_2(\mathbf{x}, \mathbf{a})} + R_2(\mathbf{x}, \mathbf{a})$$

Example (continued): Since 
$$H(\mathbf{x}) = \begin{pmatrix} -4\sin(2x_1) & 0\\ 0 & -\cos(x_2) \end{pmatrix}$$
,

$$f(\mathbf{x}) = T_1(\mathbf{x}, \mathbf{a}) + \frac{1}{2} \begin{pmatrix} x_1 - 1 \\ x_2 - 1 \end{pmatrix}^T \begin{pmatrix} -4\sin(2) & 0 \\ 0 & -\cos(1) \end{pmatrix} \begin{pmatrix} x_1 - 1 \\ x_2 - 1 \end{pmatrix} + R_2(\mathbf{x}, \mathbf{a})$$



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### MULTIVARIATE TAYLOR APPROXIMATION

- Higher order k gives a better approximation
- $T_k(\mathbf{x}, \mathbf{a})$  is the best *k*-th order approximation to  $f(\mathbf{x})$  near  $\mathbf{a}$



Consider  $T_2(\mathbf{x}, \mathbf{a}) = f(\mathbf{a}) + \nabla f(\mathbf{a})^T (\mathbf{x} - \mathbf{a}) + \frac{1}{2} (\mathbf{x} - \mathbf{a})^T H(\mathbf{a}) (\mathbf{x} - \mathbf{a})$ . The first/second/third term ensures the values/slopes/curvatures of  $T_2$  and f match at  $\mathbf{a}$ .



### TAYLOR'S THEOREM (MULTIVARIATE)

The theorem for general order *k* requires a more involved notation. **Taylor's theorem (***k***-th order):** If  $f \in C^k$ , it holds that

$$f(\mathbf{x}) = \underbrace{\sum_{|\alpha| \le k} \frac{D^{\alpha} f(\boldsymbol{a})}{\alpha!} (\mathbf{x} - \boldsymbol{a})^{\alpha}}_{T_k(\mathbf{x}, \boldsymbol{a})} + R_k(\mathbf{x}, \boldsymbol{a})$$

with 
$$R_k(\mathbf{x}, \mathbf{a}) = o(\|\mathbf{x} - \mathbf{a}\|^k)$$
 as  $\mathbf{x} \to \mathbf{a}$ .  
Notation: Multi-index  $\alpha \in \mathbb{N}^d$ 

• 
$$|\boldsymbol{\alpha}| = \alpha_1 + \dots + \alpha_d$$
  
•  $\boldsymbol{\alpha}! = \alpha_1! \dots \alpha_d!$   
•  $\boldsymbol{\alpha}^{\alpha} = x_1^{\alpha_1} \dots x_d^{\alpha_d}$   
•  $D^{\alpha} f = \frac{\partial^{|\boldsymbol{\alpha}|} f}{\partial x_1^{\alpha_1} \dots \partial x_d^{\alpha_d}}$ 

### TAYLOR'S THEOREM (MULTIVARIATE) / 2

Let us check for bivariate *f* (*d* = 2). For  $|\alpha| \leq 1$ , we have

$\alpha_1$	$\alpha_2$	$ \alpha $	$D^{\alpha}f$	lpha!	$(\mathbf{x} - \mathbf{a})^{lpha}$
0	0	0	f	1	1
1	0	1	$\partial f/\partial x_1$	1	$x_1 - a_1$
0	1	1	$\partial f/\partial x_2$	1	<i>x</i> <sub>2</sub> - <i>a</i> <sub>2</sub>



and therefore

$$T_{1}(\mathbf{x}, \mathbf{a}) = \frac{f(\mathbf{a})}{1} \cdot 1 + \frac{\partial f(\mathbf{a})}{\partial x_{1}} (x_{1} - a_{1}) + \frac{\partial f(\mathbf{a})}{\partial x_{2}} (x_{2} - a_{2})$$
$$= f(\mathbf{a}) + \left(\frac{\frac{\partial f(\mathbf{a})}{\partial x_{1}}}{\frac{\partial f(\mathbf{a})}{\partial x_{2}}}\right)^{T} \begin{pmatrix} x_{1} - a_{1} \\ x_{2} - a_{2} \end{pmatrix}$$
$$= f(\mathbf{a}) + \nabla f(\mathbf{a})^{T} (\mathbf{x} - \mathbf{a}).$$

### **TAYLOR SERIES (MULTIVARIATE)**

Analogous to univariate case, if *f* ∈ C<sup>∞</sup>, there *might* exist an open ball B<sub>r</sub>(a) with radius *r* > 0 around a such that the Taylor series

$$\sum_{|\boldsymbol{\alpha}|\geq 0} \frac{D^{\boldsymbol{\alpha}} f(\boldsymbol{a})}{\boldsymbol{\alpha}!} (\mathbf{x} - \boldsymbol{a})^{\boldsymbol{\alpha}}$$

converges to f on  $B_r(\mathbf{a})$ 

- Even if Taylor series converges, it might not converge to f
- Upper bound R = sup {r | Taylor series converges on B<sub>r</sub>(a)} is called the radius of convergence of Taylor series around a
- If *R* > 0 and *f* analytic, Taylor series converges *absolutely* and *uniformly* to *f* on *compact* sets inside *B<sub>R</sub>(a)*
- No general convergence behaviour on boundary of  $B_R(a)$

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