

Smoothness Analysis for Probabilistic Programs with Application to Optimised Variational Inference



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³KAIST, South Korea

Part 1

Smoothness Analysis for Probabilistic Programs
with Application to Optimised Variational Inference

Part 2



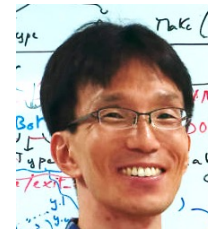
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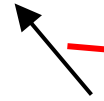
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Why Care About Smoothness?

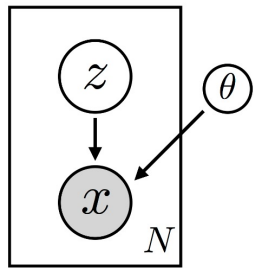
“Smoothness” = {differentiability, Lipschitz continuity, continuity, ...}.

~~infinitely differentiable (in mathematics)~~



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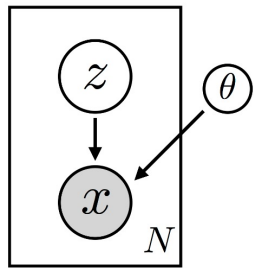


probabilistic model

Can apply many inference algorithms.

Why Care About Smoothness?

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differentiable

probabilistic model

Can apply **more efficient** inference algorithms.

$$\begin{aligned} \nabla_{\theta} \mathbb{E}_{p(\mathbf{x}; \theta)} [f(\mathbf{x})] \\ = \mathbb{E}_{p(\epsilon)} [\nabla_{\theta} f(g(\epsilon; \theta))] \end{aligned}$$

pathwise gradient estimator

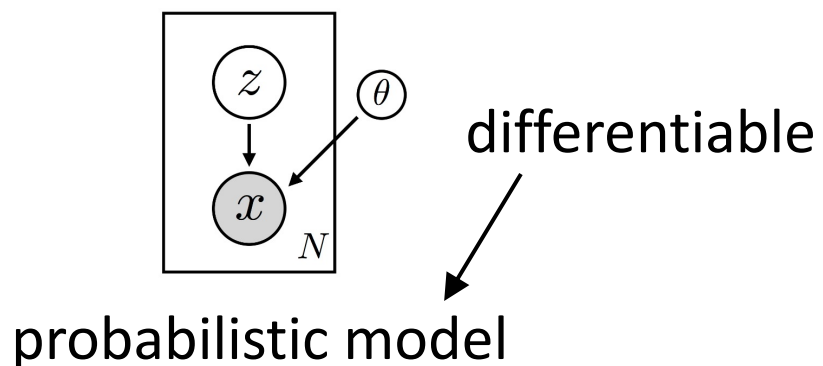
$$\begin{aligned} \frac{dq_i}{dt} &= \frac{\partial H}{\partial p_i} \\ \frac{dp_i}{dt} &= -\frac{\partial H}{\partial q_i} \end{aligned}$$

Hamiltonian Monte Carlo

...

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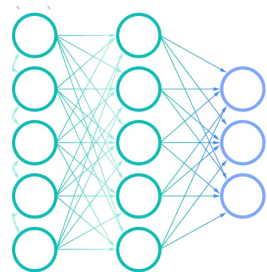
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Lipschitz continuous

neural network

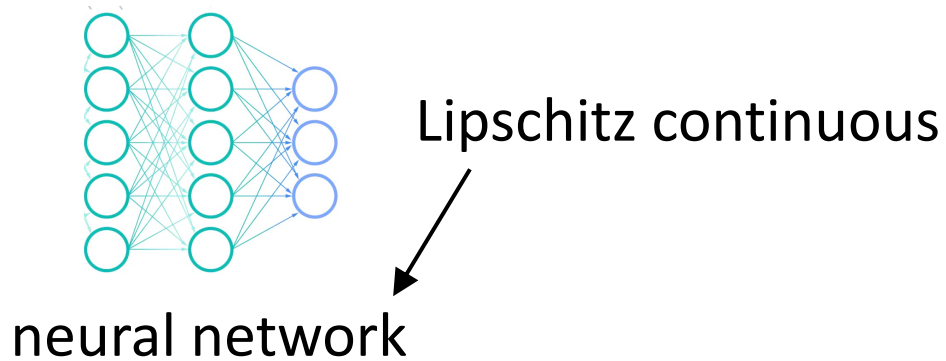
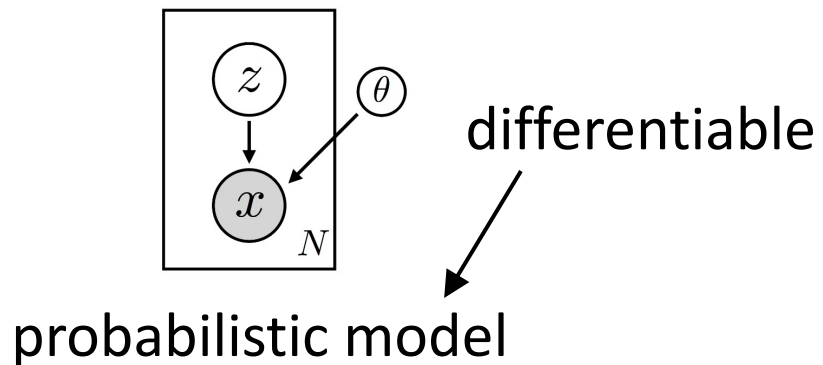
Can provide provable robustness.

Can give guaranteed generalization bounds.

...

Why Care About Smoothness?

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... many more examples!

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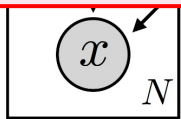
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...

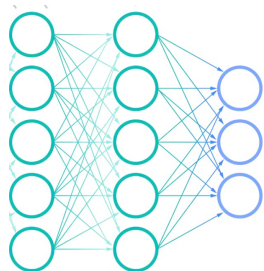
Why Care About Smoothness?

“Smoothness” = {differentiability, Lipschitz continuity, continuity, ...}.

Goal: Find out smoothness properties, automatically and soundly.



probabilistic model



neural network

... many more examples!

$$= \mathbb{E}_{p(\epsilon)} [\nabla_{\theta} f(g(\epsilon; \theta))]$$

pathwise gradient estimator

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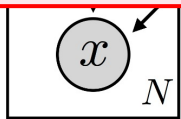
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Why Care About Smoothness?

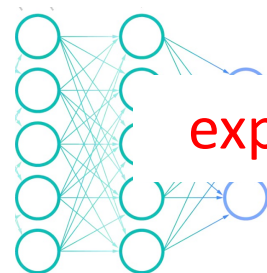
“Smoothness” = {differentiability, Lipschitz continuity, continuity, ...}.

of programs

Goal: Find out smoothness properties, automatically and soundly.



probabilistic model



neural network

expressed by programs

... many more examples!

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pathwise gradient estimator

$$\frac{dp_i}{dt} = -\frac{\partial H}{\partial q_i}$$

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Smoothness Properties of Programs

Smoothness = **differentiability**. Programs = **deterministic, imperative** programs.

Smoothness Properties of Programs

Smoothness = differentiability. Programs = deterministic, imperative programs.

$P \triangleq (y := \exp(x) ; \text{if } (x > 0) \{z := 1\} \text{ else } \{z := -1\})$

real-valued

The diagram shows the text 'real-valued' in red at the bottom center. Three red arrows originate from this text and point upwards to the following elements in the program definition: the expression 'exp(x)', the condition '(x > 0)', and the assignment '{z := -1}'.

Smoothness Properties of Programs

Smoothness = differentiability. Programs = deterministic, imperative programs.

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• $[[P]] : \mathbb{R}^3 \rightarrow \mathbb{R}^3$

$$\begin{pmatrix} x \\ y \\ z \end{pmatrix} \mapsto \begin{pmatrix} x' \\ y' \\ z' \end{pmatrix} = \begin{pmatrix} x \\ \exp(x) \\ \text{sgn}(x) \end{pmatrix}$$

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- $P \vdash y$ is differentiable in x

$\iff \dots$

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\Leftrightarrow

$$\begin{pmatrix} x \\ y_0 \\ z_0 \end{pmatrix} \xrightarrow{\llbracket P \rrbracket} \begin{pmatrix} x' \\ y' \\ z' \end{pmatrix}$$

for all $y_0, z_0 \in \mathbb{R}$.

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$$\Leftrightarrow f : \mathbb{R} \rightarrow \mathbb{R}$$

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$\Leftrightarrow f : \mathbb{R} \rightarrow \mathbb{R}$ is differentiable for all $y_0, z_0 \in \mathbb{R}$.

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- $P \vdash y$ is differentiable in x .

- $P \not\vdash z$ is differentiable in x .

- ...

Smoothness Properties of Programs

Smoothness = differentiability. Programs = deterministic, imperative programs.

$$P \triangleq (y := \exp(x) ; \text{if } (x > 0) \{z := 1\} \text{ else } \{z := -1\})$$

It is surprisingly subtle to find out such smoothness properties

- (1) automatically,
- (2) soundly, and
- (3) precisely enough.

Differentiability Analysis (Composition Case)

Want to check differentiability of a program in a **compositional** way.

Challenging case: Given P, P' and $U, V \subseteq \text{Var}$, want to check

$$\forall u \in U, \forall v \in V. \quad P; P' \vdash u \text{ is differentiable in } v.$$

Differentiability Analysis (Composition Case)

Based on the chain rule:

$$\begin{array}{l} \exists T \subseteq \text{Var.} \\ \forall u \in U, \forall t \in T. \quad P' \vdash u \text{ is differentiable in } t \\ \forall t \in T, \forall v \in V. \quad P \vdash t \text{ is differentiable in } v \\ \hline \forall u \in U, \forall v \in V. \quad P; P' \vdash u \text{ is differentiable in } v \end{array}$$

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- Looks sound by chain rule.
- Previously considered:
e.g., [CACM'12] for continuity.

Seq

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Is this rule indeed sound?

Issue 1: Soundness

$P;P' \triangleq (y := \text{sgn}(x) ; z := x+y).$

$\forall u \in U, \forall t \in T. \quad P' \vdash u \text{ is differentiable in } t$

$\forall t \in T, \forall v \in V. \quad P \vdash t \text{ is differentiable in } v$

$\forall u \in U, \forall v \in V. \quad P;P' \vdash u \text{ is differentiable in } v$ Seq

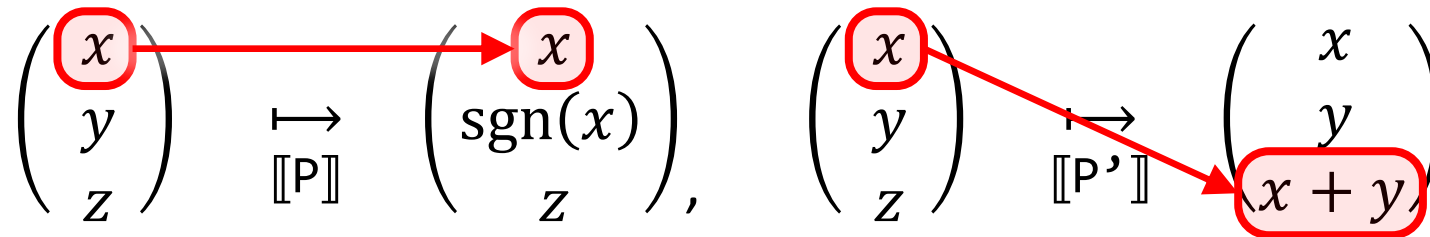
$$\begin{pmatrix} x \\ y \\ z \end{pmatrix} \xrightarrow{\llbracket P \rrbracket} \begin{pmatrix} x \\ \text{sgn}(x) \\ z \end{pmatrix}, \quad \begin{pmatrix} x \\ y \\ z \end{pmatrix} \xrightarrow{\llbracket P' \rrbracket} \begin{pmatrix} x \\ y \\ x + y \end{pmatrix}$$

Issue 1: Soundness

$P;P' \triangleq (y := \text{sgn}(x) ; z := x+y).$ $U \triangleq \{z\}, T \triangleq \{x\}, V \triangleq \{x\}.$

✓ $\forall u \in U, \forall t \in T. \quad P' \vdash u$ is differentiable in t
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$\forall u \in U, \forall v \in V. \quad P;P' \vdash u$ is differentiable in v Seq



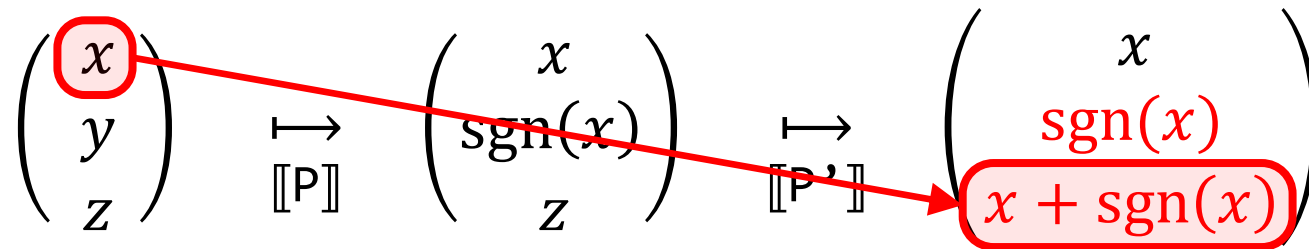
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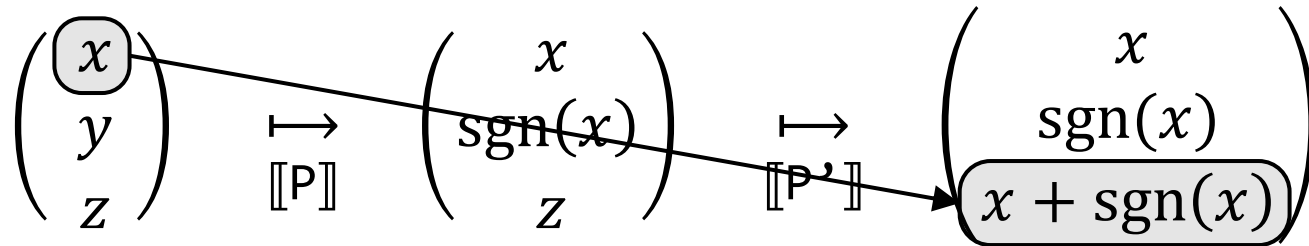


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- Seq



This rule is unsound! But why?

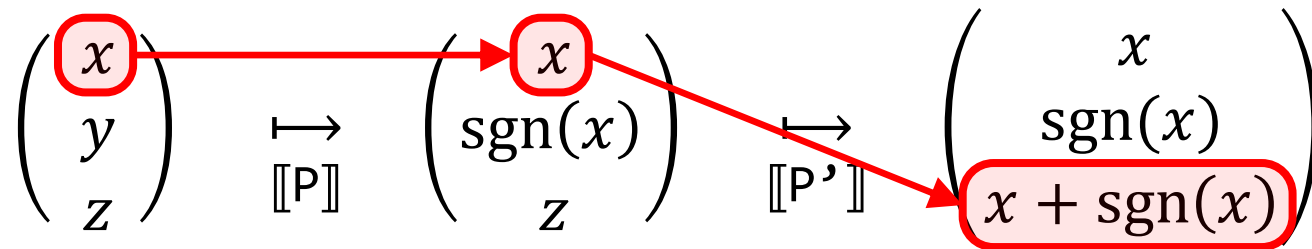
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Issue 1: Soundness

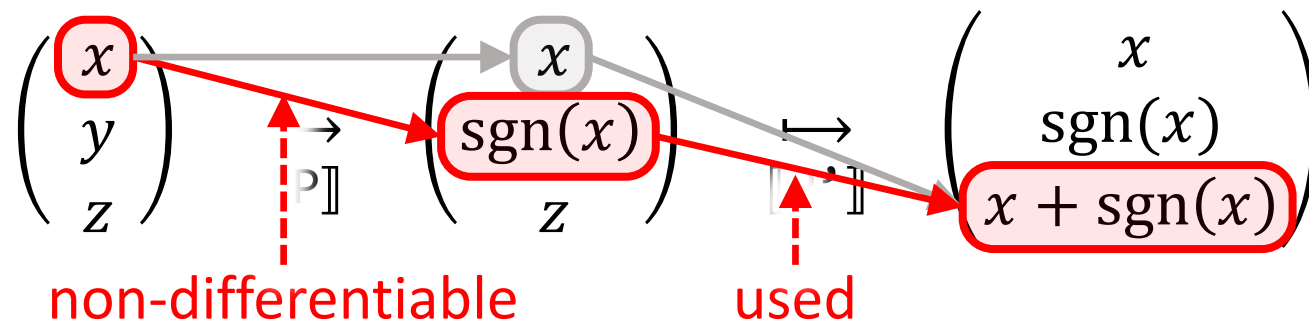
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Seq

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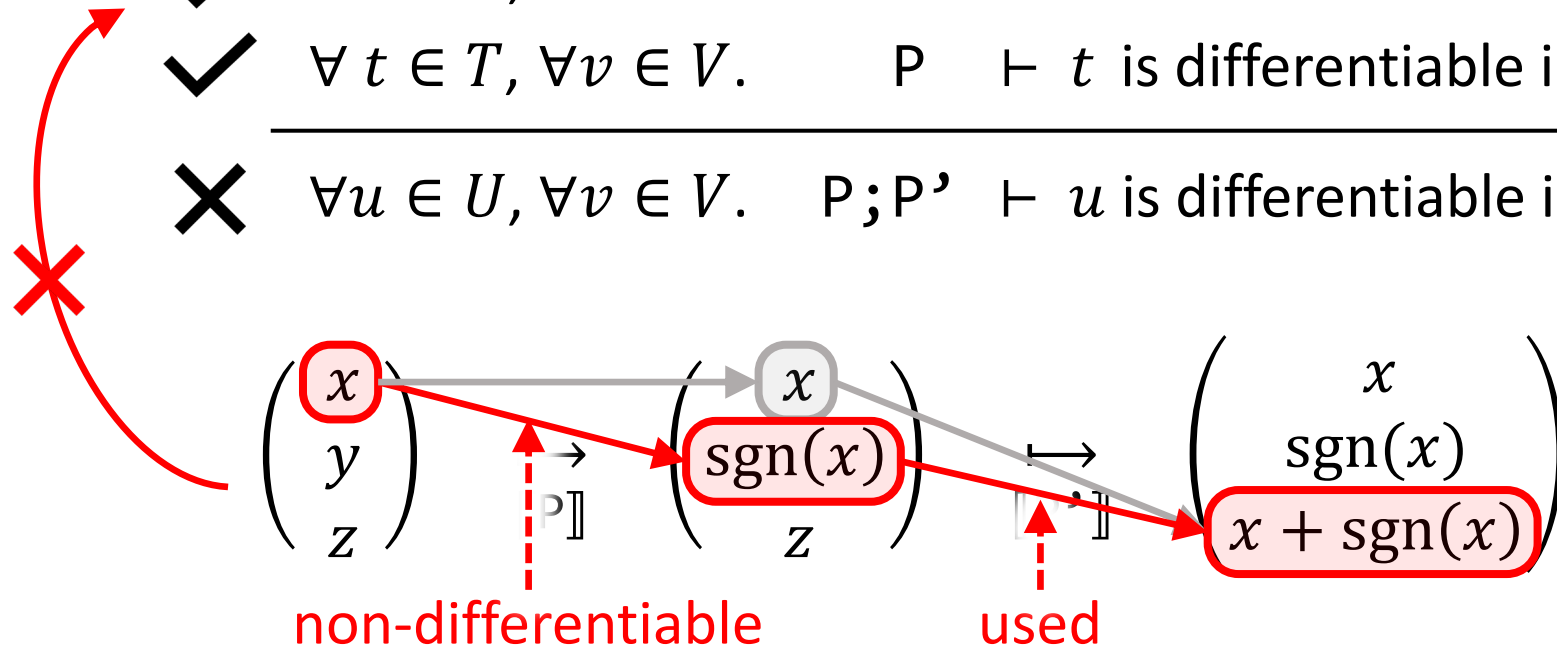


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Issue 1: Soundness

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 $\times \quad \forall u \in U, \forall v \in V. \quad P;P' \vdash u \text{ is differentiable in } v$ Seq

Lesson: Need to consider dependency between variables.

non-differentiable

used

Issue 1: Possible Fix

$P;P' \triangleq (y := \text{sgn}(x) ; z := x+y).$ $U \triangleq \{z\}, \underline{T \triangleq \{x\}}, V \triangleq \{x\}.$

$$\frac{\forall u \in U, \forall t \in \underline{T} \quad P' \vdash u \text{ is differentiable in } t \quad \forall t \in \underline{T}, \forall v \in V. \quad P \vdash t \text{ is differentiable in } v}{\forall u \in U, \forall v \in V. \quad P;P' \vdash u \text{ is differentiable in } v} \text{Seq'}$$

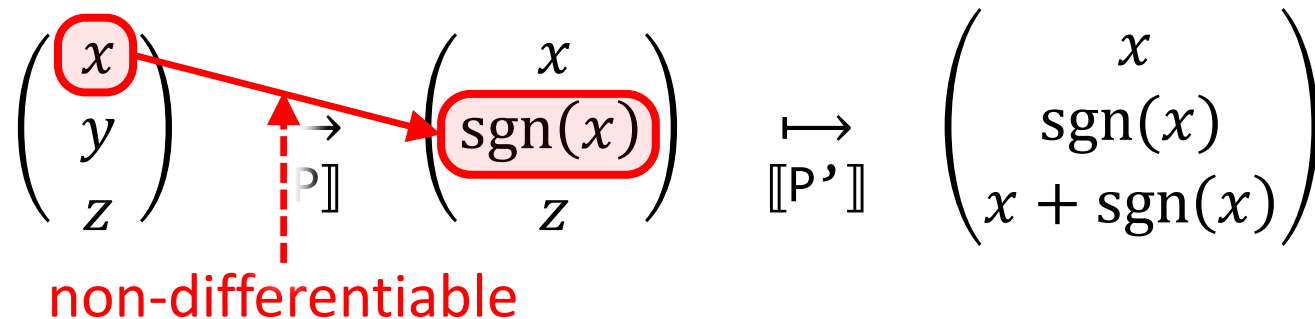
X $\forall u \in U, \forall v \in V. \quad P;P' \vdash u \text{ is differentiable in } v$

$$\begin{pmatrix} x \\ y \\ z \end{pmatrix} \xrightarrow{\llbracket P \rrbracket} \begin{pmatrix} x \\ \text{sgn}(x) \\ z \end{pmatrix} \xrightarrow{\llbracket P' \rrbracket} \begin{pmatrix} x \\ \text{sgn}(x) \\ x + \text{sgn}(x) \end{pmatrix}$$

Issue 1: Possible Fix

$P;P' \triangleq (y := \text{sgn}(x) ; z := x+y).$ $U \triangleq \{z\}, \cancel{T \triangleq \{x\}}, V \triangleq \{x\}.$

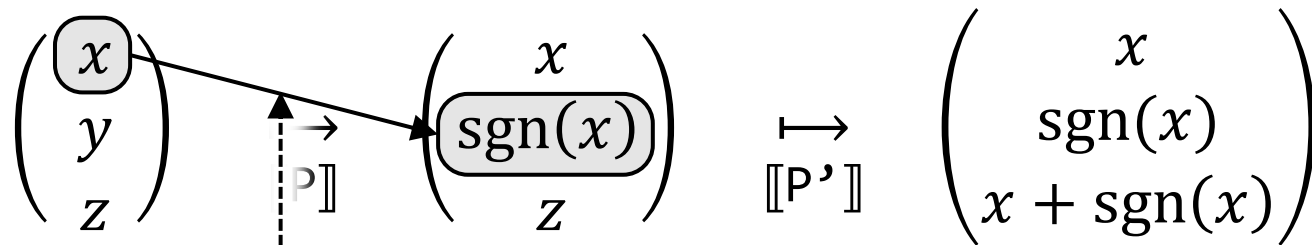
$$\begin{array}{c}
 \text{Var} \\
 \swarrow \quad \searrow \\
 \forall u \in U, \forall t \in \cancel{T} \quad P' \vdash u \text{ is differentiable in } t \\
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 \end{array}$$



This rule now looks sound. Are we done?

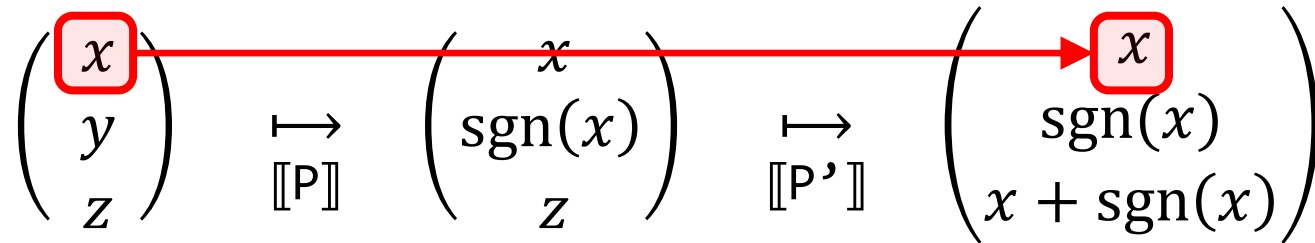
Issue 2: Precision

$P;P' \triangleq (y := \text{sgn}(x) ; z := x+y).$ $U \triangleq \{x\}, T \triangleq \{x\}, V \triangleq \{x\}.$

Var

$\forall u \in U, \forall t \in T.$ $P' \vdash u$ is differentiable in t
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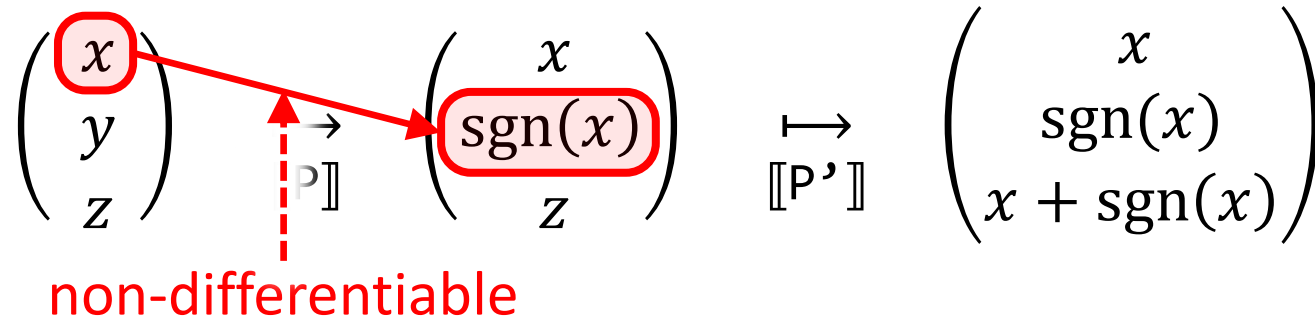
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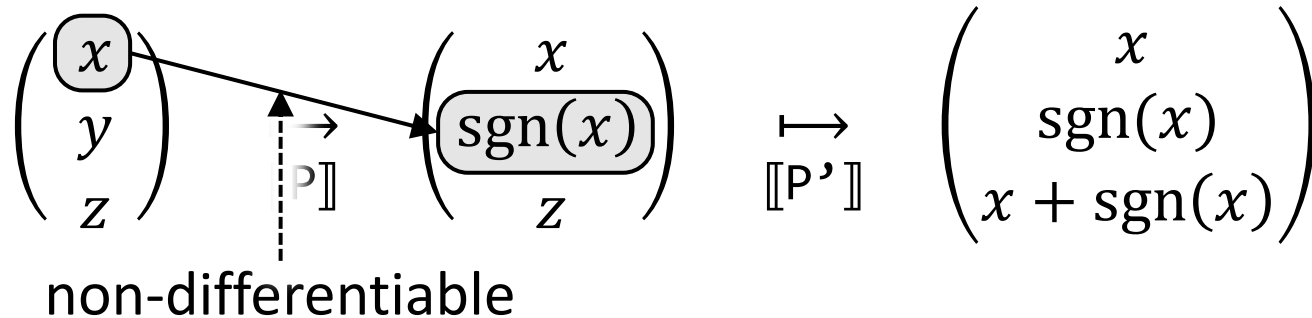
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 \end{array}$$



Issue 2: Precision

$$P;P' \triangleq (y := \text{sgn}(x) ; z := x+y). \quad U \triangleq \{x\}, \quad \underline{T} \triangleq \{x\}, \quad V \triangleq \{x\}.$$

cannot deduce \rightarrow

$$\begin{array}{c}
 \text{Var} \\
 \swarrow \quad \searrow \\
 \forall u \in U, \forall t \in \underline{T}. \quad P' \vdash u \text{ is differentiable in } t \\
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 \hline
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 \end{array}$$


This rule is too imprecise!

Issue 2: Precision

$$\frac{\begin{array}{l} \forall u \in U, \forall t \in \text{Var.} \quad P' \vdash u \text{ is differentiable in } t \\ \forall t \in \text{Var}, \forall v \in V. \quad P \vdash t \text{ is differentiable in } v \end{array}}{\forall u \in U, \forall v \in V. \quad P; P' \vdash u \text{ is differentiable in } v} \text{Seq}'$$

Admit the imprecision for now.
Is this rule indeed sound?

Issue 3: Soundness (Again)

$$P;P' \triangleq (y:=x ; z:=f(x,y)) \text{ for } f(x,y) \triangleq \begin{cases} xy/(x^2 + y^2) & \text{if } (x,y) \neq (0,0) \\ 0 & \text{if } (x,y) = (0,0). \end{cases}$$

$$\frac{\begin{array}{l} \forall u \in U, \forall t \in \text{Var}. \quad P' \vdash u \text{ is differentiable in } t \\ \forall t \in \text{Var}, \forall v \in V. \quad P \vdash t \text{ is differentiable in } v \end{array}}{\forall u \in U, \forall v \in V. \quad P;P' \vdash u \text{ is differentiable in } v} \text{Seq}'$$

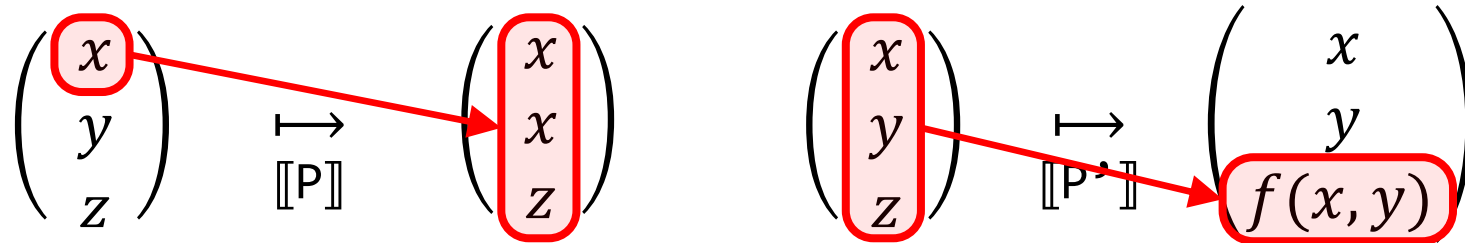
$$\begin{pmatrix} x \\ y \\ z \end{pmatrix} \xrightarrow{[[P]]} \begin{pmatrix} x \\ x \\ z \end{pmatrix} \quad \begin{pmatrix} x \\ y \\ z \end{pmatrix} \xrightarrow{[[P']] } \begin{pmatrix} x \\ y \\ f(x,y) \end{pmatrix}$$

Issue 3: Soundness (Again)

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$U \triangleq \{z\}, V \triangleq \{x\}.$

$$\begin{array}{l} \checkmark \quad \forall u \in U, \quad \forall t \in \text{Var}. \quad P' \vdash u \text{ is differentiable in } t \\ \checkmark \quad \forall t \in \text{Var}, \forall v \in V. \quad P \vdash t \text{ is differentiable in } v \\ \hline \forall u \in U, \forall v \in V. \quad P;P' \vdash u \text{ is differentiable in } v \end{array} \text{Seq}'$$



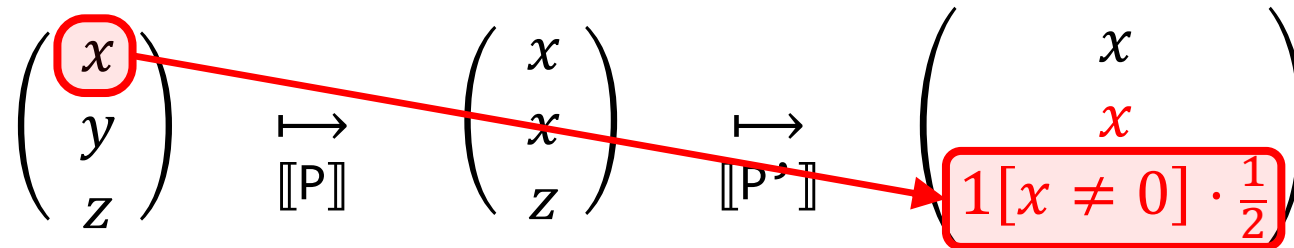
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- ✓ $\forall u \in U, \forall t \in \text{Var}. P' \vdash u$ is differentiable in t
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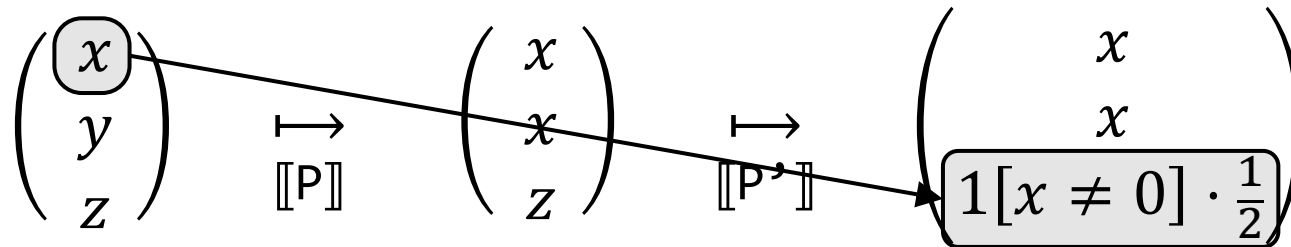
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This rule is still unsound! But why?

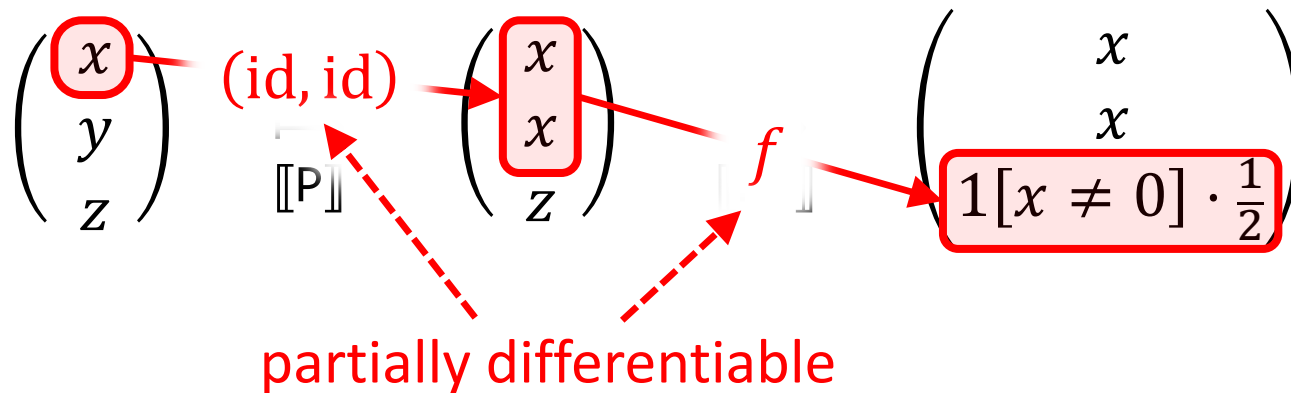
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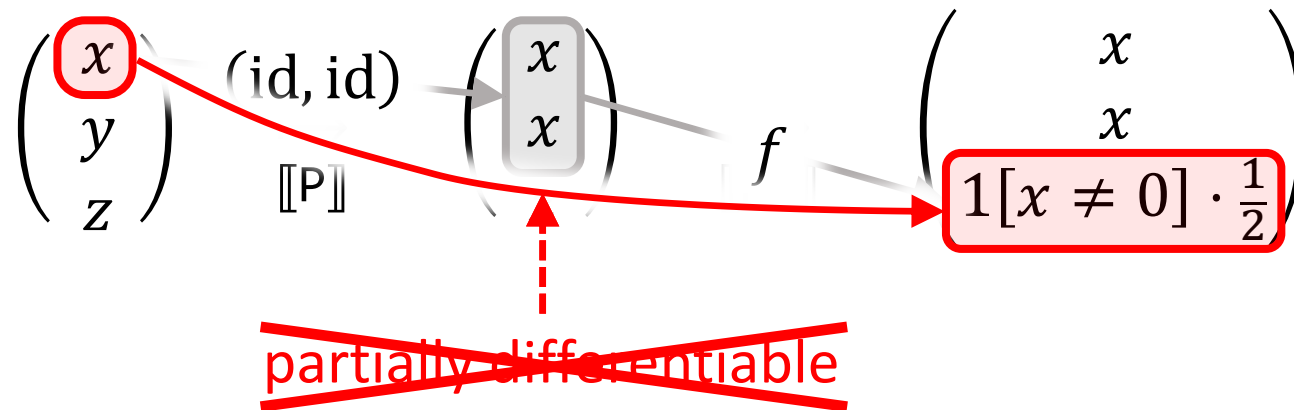
Issue 3: Soundness (Again)

$P;P' \vdash u$ is differentiable in t if $(x, y) \neq (0,0)$
 $U \triangleq \{z\}$

Fact: g, h are partially differentiable $\not\Rightarrow g \circ h$ does so.

- ✓ $\forall u \in U, \forall t \in \text{Var}. P' \vdash u$ is differentiable in t
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- ✗ $\forall u \in U, \forall v \in V. P;P' \vdash u$ is differentiable in v Seq'



Issue 3: Soundness (Again)

$P;P' \triangleq (y: \dots)$
 $U \triangleq \{z\}, V \triangleq \dots$

$g, h \text{ are partially differentiable} \Rightarrow g \circ h \text{ does so.}$

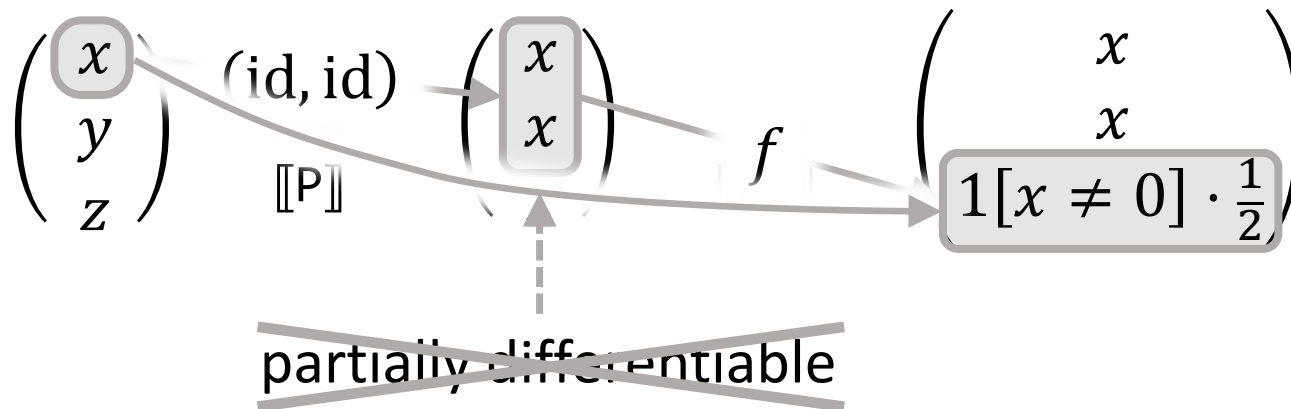
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assumed implicitly,
but invalid.

Seq'



Issue 3: Soundness (Again)

$P;P' \triangleq (y: U \triangleq \{z\}, V \triangleq \dots)$

$g, h \text{ are partially differentiable} \Rightarrow g \circ h \text{ does so.}$

$(\dots) \text{ if } (x, v) \neq (0,0) \Rightarrow (0,0).$

✓ $\forall u \in U, \forall t \in \text{Var}. P' \vdash u \text{ is differentiable in } t$

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✗ $\forall u \in U, \forall v \in V. P;P' \vdash u \text{ is differentiable in } v$

Lesson: Need to identify & check assumptions on target smoothness.

~~partially differentiable~~

It is subtle to do smoothness analysis, soundly and precisely.

→ Our approach for smoothness analysis

Our Approach: Smoothness Property

$P \vdash U$ is ϕ -smooth in V ($U, V \subseteq \text{Var}$)

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- $P \vdash \{x, y, z\}$ is ϕ -smooth in $\{y, z\}$
 $\iff \dots$

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• $P \vdash \{x, y, z\}$ is ϕ -smooth **in $\{y, z\}$**

\Leftrightarrow

for any $x_0 \in \mathbb{R}$.

$$\begin{pmatrix} x_0 \\ y \\ z \end{pmatrix} \xrightarrow{[[P]]} \begin{pmatrix} x' \\ y' \\ z' \end{pmatrix}$$

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• $P \vdash \{x, y, z\}$ is ϕ -smooth in $\{y, z\}$

$\Leftrightarrow f: \mathbb{R}^2 \rightarrow \mathbb{R}^3$ for any $x_0 \in \mathbb{R}$.

$$\begin{pmatrix} x_0 \\ y \\ z \end{pmatrix} \xrightarrow{[[P]]} \begin{pmatrix} x' \\ y' \\ z' \end{pmatrix}$$

Our Approach: Smoothness Property

$$P \vdash U \text{ is } \phi\text{-smooth in } V \quad (U, V \subseteq \text{Var})$$

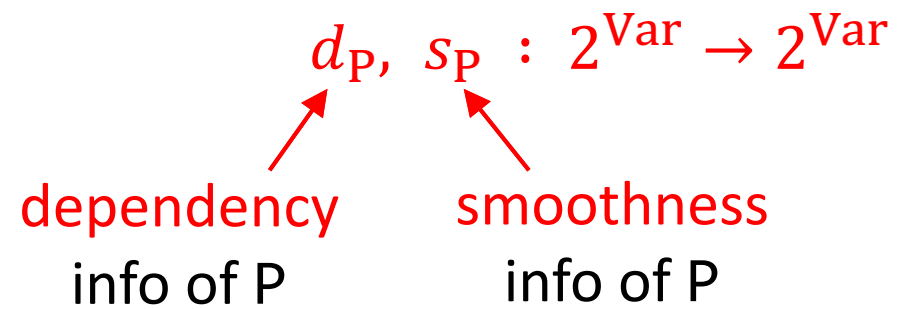
- $\phi \subseteq \{f: \mathbb{R}^n \rightarrow \mathbb{R}^m\}$: any set of “smooth” functions.
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- $P \vdash \{x, y, z\}$ is ϕ -smooth in $\{y, z\}$

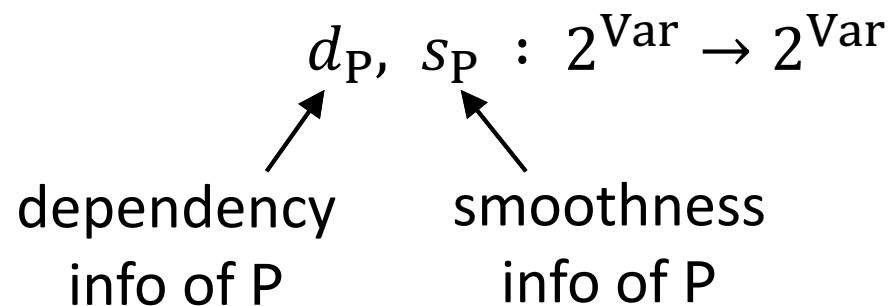
$$\iff f: \mathbb{R}^2 \rightarrow \mathbb{R}^3 \in \phi \text{ for any } x_0 \in \mathbb{R}.$$

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Our Approach: Smoothness Analysis

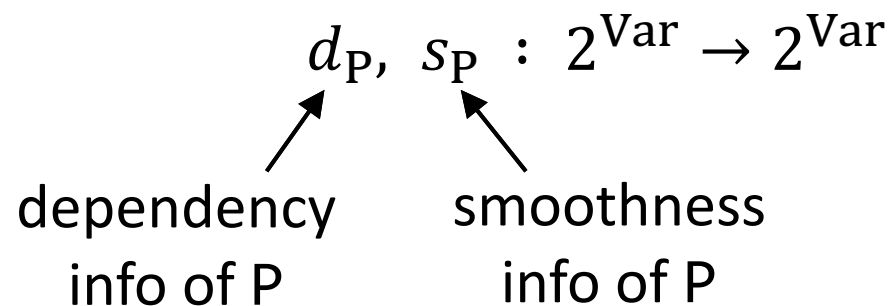


Our Approach: Smoothness Analysis



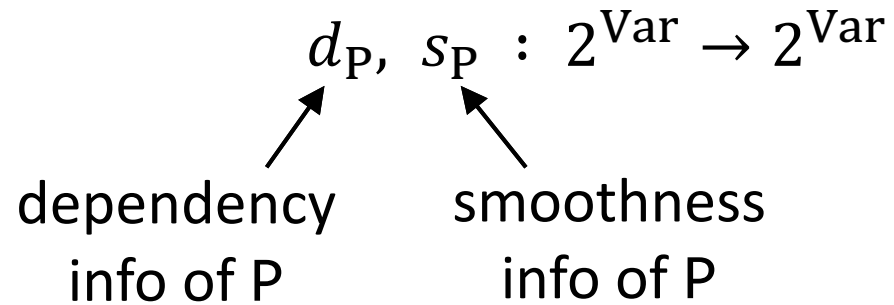
- **Invariants:** $P \vdash V$ is **dependent** at most on $d_P(V)$.
- $P \vdash V$ is **ϕ -smooth** in $s_P(V)$.

Our Approach: Smoothness Analysis



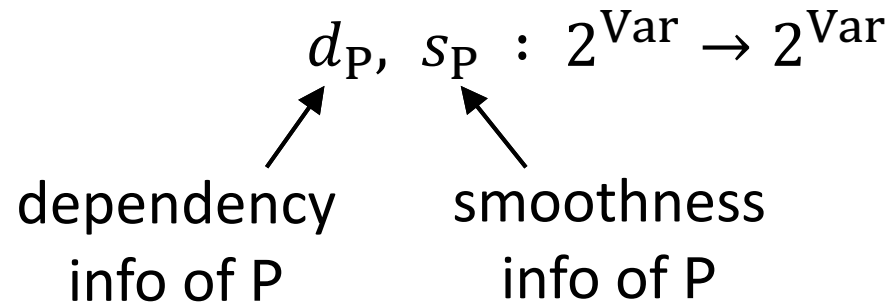
- Invariants: $P \vdash V$ is dependent at most on $d_P(V)$.
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 $s_{P;P'}(V) \triangleq s_P(d_{P'}(V)) \cap d_P(s_{P'}(V)^c)^c$.

Our Approach: Smoothness Analysis



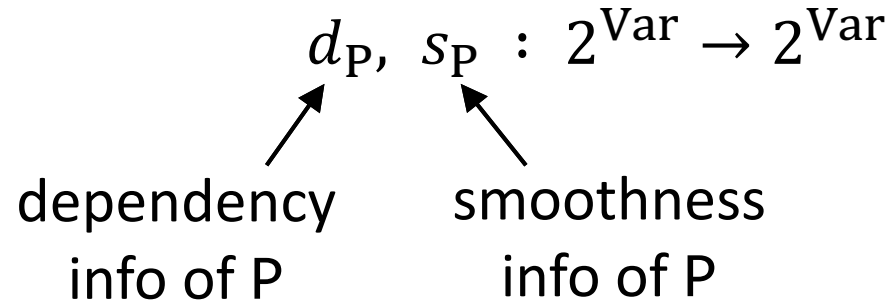
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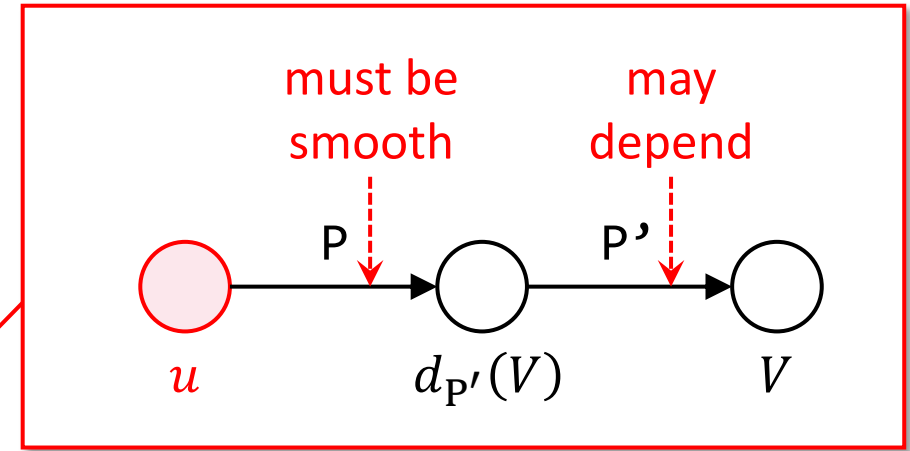
$$\underbrace{s_{P;P'}(V)}_{u \in} \triangleq \underbrace{s_P(d_{P'}(V))}_{u \in} \wedge \underbrace{d_P(s_{P'}(V)^c)^c}_{u \in}$$

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Our Approach: Smoothness Analysis

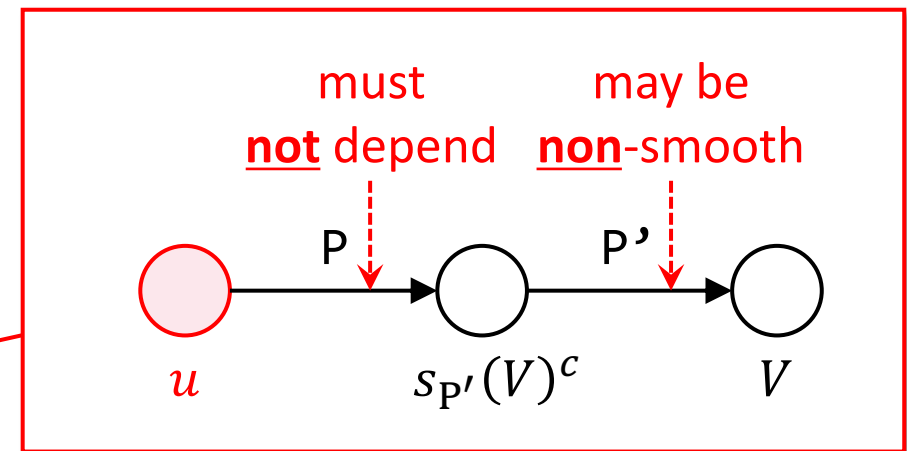
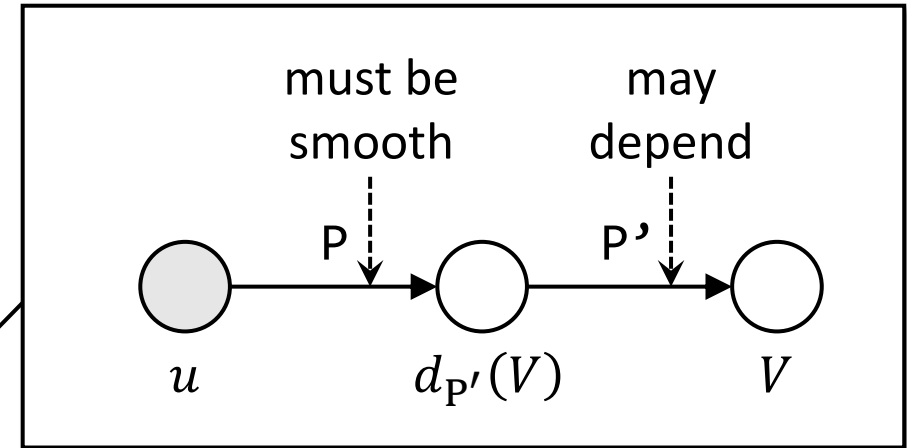
$d_P, s_P : 2^{\text{Var}} \rightarrow 2^{\text{Var}}$
 dependency info of P smoothness info of P

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 $P \vdash V$ is ϕ -smooth in $s_P(V)$.

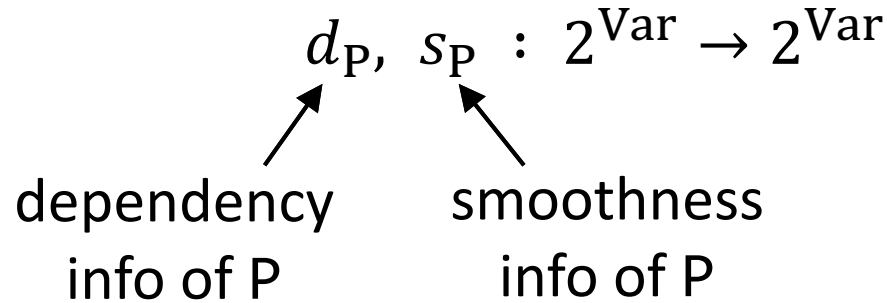
- Rules:

$$d_{P;P'}(V) \triangleq d_P(d_{P'}(V)).$$

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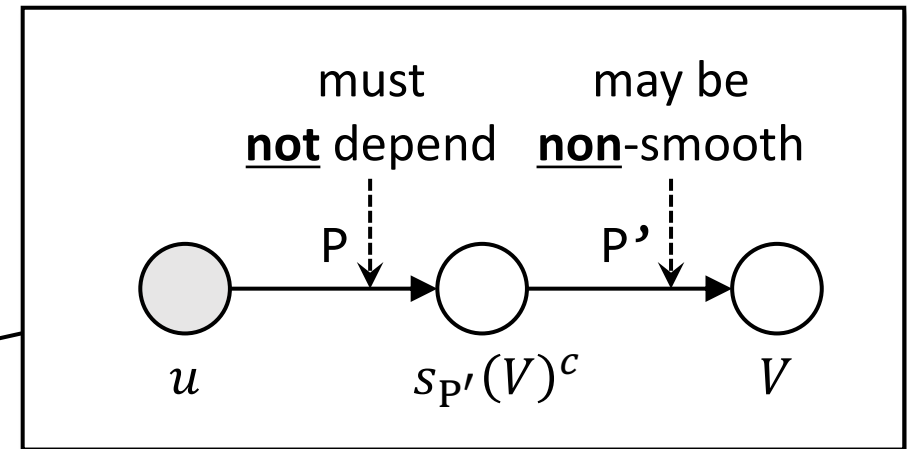
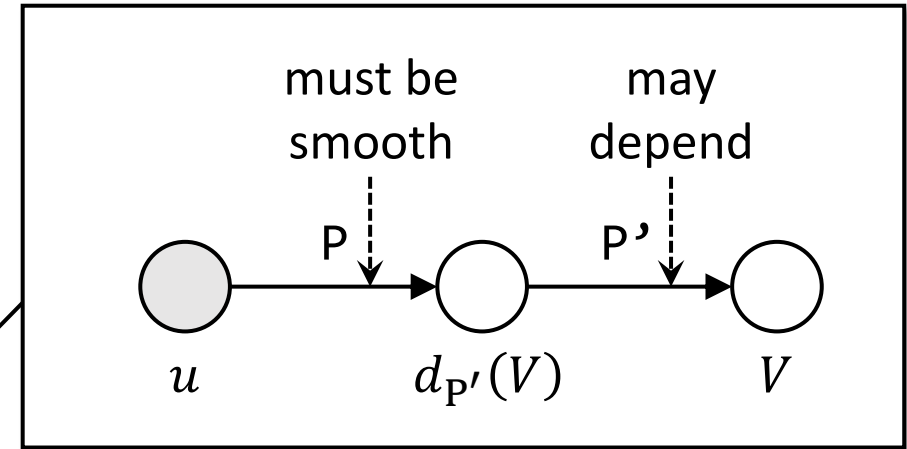
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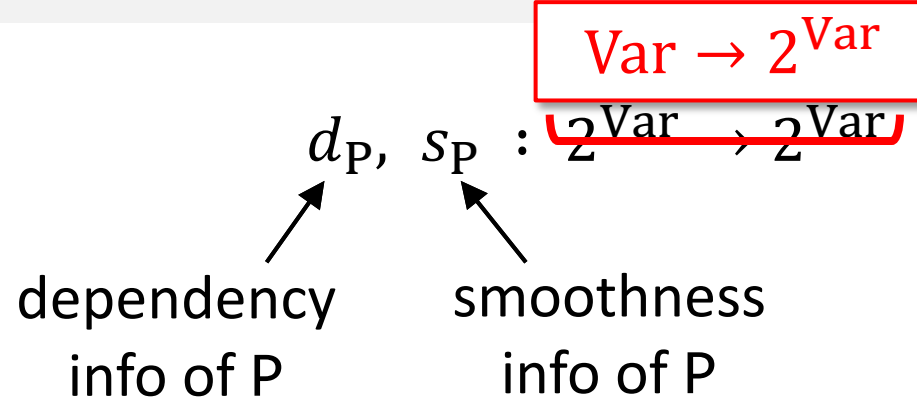
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\Rightarrow can apply the chain rule



Our Approach: Smoothness Analysis



- Invariants:

P : first-order, imperative language
(+ probabilistic prog. constructs)

- Rules:

$$d_{P;P'}(V) \triangleq d_P(d_{P'}(V)).$$

$s_{P;P'}$
 $u \in$

More details are in the paper.

Our Approach: Soundness

Theorem Our ϕ -smoothness analysis is sound if ϕ satisfies five assumptions:

- ...
- ...
- ...
- ...
- ...

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- **Composition:** $\forall f: \mathbb{R}^n \rightarrow \mathbb{R}^m, g: \mathbb{R}^m \rightarrow \mathbb{R}^l. \quad f, g \in \phi \implies (g \circ f) \in \phi.$
- **Pairing:** $\forall f: \mathbb{R}^n \rightarrow \mathbb{R}^m, g: \mathbb{R}^n \rightarrow \mathbb{R}^l. \quad f, g \in \phi \implies (f, g) \in \phi.$
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• ...	Target smoothness property	A3 (proj.)	A4 (pair.)	A5 (rest.)	A6 (comp.)	A7 (stri.)
• ...	cont. (C^0)	○	○	○	○	○
• ...	locally Lipschitz (= $\phi^{(l)}$)	○	○	○	○	○
• ...	uniformly cont.	○	○	○	○	○
	Lipschitz cont.	○	○	○	○	○
	jointly diff.	○	○	○	○	○
	continuously diff. (C^1)	○	○	○	○	○
	smooth (C^∞)	○	○	○	○	○
	real analytic (C^ω)	○	○	○	○	○
	partially cont. (= $\phi^{(pc)}$)	○	○	○	✗	○
	partially diff. (= $\phi^{(pd)}$)	○	○	○	✗	○
	almost-everywhere cont.	○	○	✗	✗	○
	almost-everywhere diff.	○	○	✗	✗	○
	coordinatewise non-decreasing	○	○	○	○	○
	locally bounded	○	○	○	○	○
	bounded	✗	○	○	○	○
	Borel measurable	○	○	○	○	○

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	locally bounded	○	○	○	○	○
	bounded	✗	○	○	○	○
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• ...

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locally bounded	○	○	○	○	○
bounded	✗	○	○	○	○
Borel measurable	○	○	○	○	○

Part 1

Smoothness Analysis for Probabilistic Programs
with Application to **Optimised Variational Inference**

Part 2



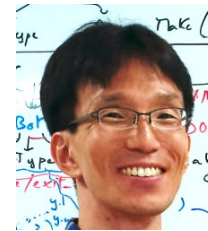
Wonyeol Lee¹

¹Stanford, USA



Xavier Rival²

²INRIA/ENS/CNRS, France



Hongseok Yang³

³KAIST, South Korea

Variational Inference

- Problem: Given probability density functions $p(z, x)$ and $q_\theta(z)$,

$$\text{minimize } \mathcal{L}(\theta) \triangleq \mathbb{E}_{q_\theta(z)} \left[\log \frac{q_\theta(z)}{p(z, x)} \right] \quad \text{over } \theta \in \mathbb{R}^n.$$

- Typical approach: Apply a gradient descent algorithm.

$$\theta_{t+1} := \theta_t - \eta \cdot \nabla_\theta \mathcal{L}(\theta_t).$$

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↑
difficult to compute, so only estimate.

Gradient Estimators

- **Basic estimator** (called score estimator):

$$\nabla_{\theta} \mathcal{L}(\theta) \approx \dots$$

for $z \sim q_{\theta}(-)$.

- **“Optimized” estimator** (called pathwise gradient estimator):

$$\nabla_{\theta} \mathcal{L}(\theta) \approx \dots$$

for $z \sim r(-)$.

Gradient Estimators

- **Basic estimator** (called score estimator):

$$\nabla_{\theta} \mathcal{L}(\theta) \approx \log \frac{q_{\theta}(z)}{p(z, x)} \times \nabla_{\theta} (\log q_{\theta}(z)) \quad \text{for } z \sim q_{\theta}(-).$$

- **“Optimized” estimator** (called pathwise gradient estimator):

$$\nabla_{\theta} \mathcal{L}(\theta) \approx \nabla_{\theta} \left(\log \frac{q_{\theta}(t_{\theta}(z))}{p(t_{\theta}(z), x)} \right) \quad \text{for } z \sim r(-).$$

Gradient Estimators

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To do so soundly, we need to know **differentiable parts** of $q_{\theta}(z)$ and $p(z, x)$.

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Part 1 is used here.

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Evaluation Results

PL for variational inference
(with neural nets, ...)

of "optimized" random var's

Example in Pyro	LoC	Our optimizer	Pyro's default optimizer	
		# rv (Sound)	# rv (Sound)	# rv (Unsound)
Splitting normal	16			
... (7 examples omitted)	...			
Deep exponential family	105			
Deep Markov model	112			
Hidden Markov model	137			
Single-cell annotation	147			
Attend-infer-repeat	174			
Conditional VAE	205			

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- Ours checks req's using smoothness analysis.
- Pyro does not check req's, so it can be unsound.

Evaluation Results

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of "optimized" random var's

Example in Pyro	LoC	# of "optimized" random var's		
		Our optimizer # rv (Sound)	Pyro's default optimizer # rv (Sound) # rv (Unsound)	
Splitting normal	16	1	1	1
... (7 examples omitted)
Deep exponential family	105	6	6	0
Deep Markov model	112	1	1	0
Hidden Markov model	137	2	2	0
Single-cell annotation	147	3	3	0
Attend-infer-repeat	174	1	1	1
Conditional VAE	205	1	1	0

Evaluation Results

PL for variational inference
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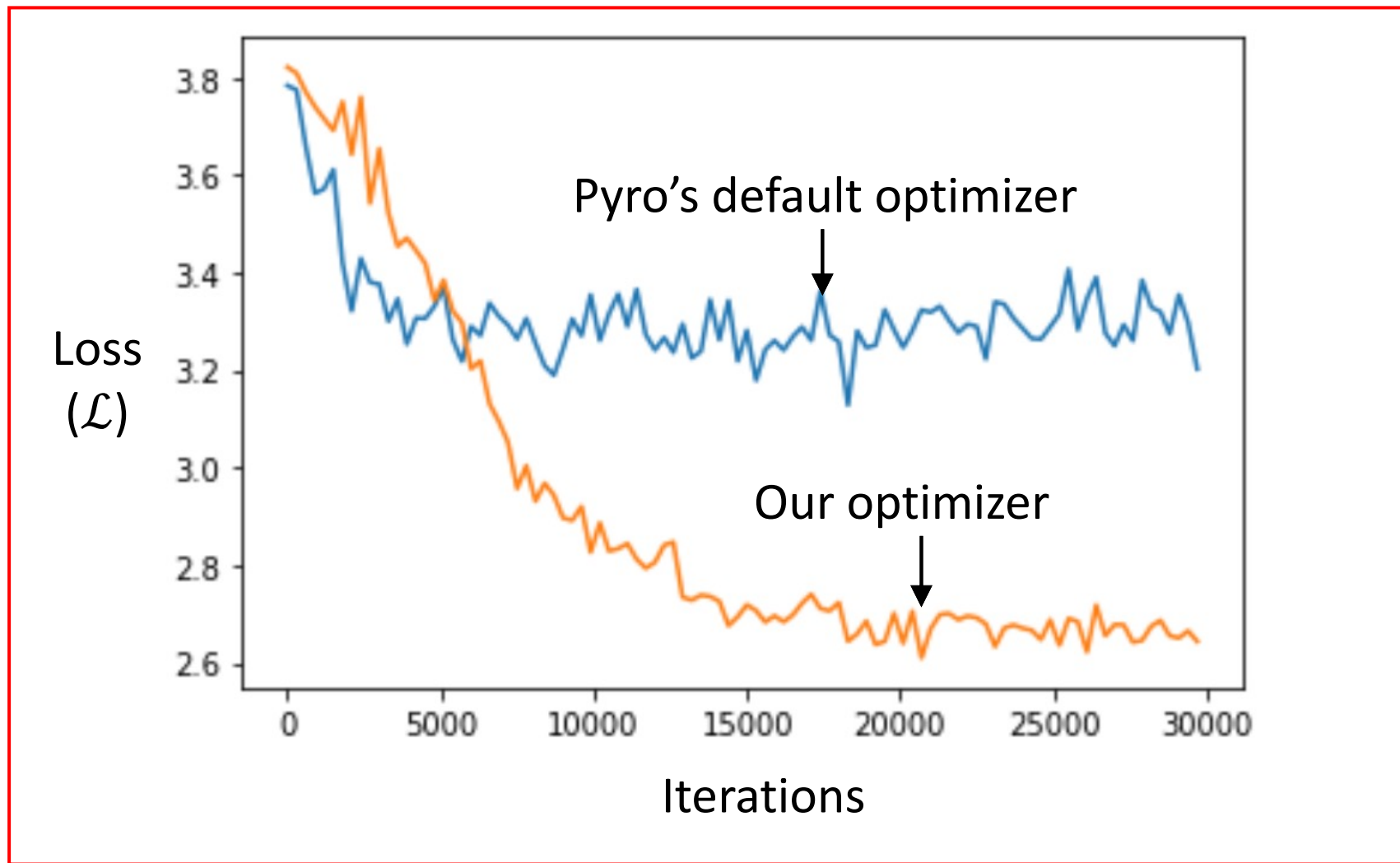
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due to branching

due to div-by-0

Evaluation Results



random var's

default optimizer

rv (Unsound)

1

...

0

0

0

0

1

0

due to branching

due to div-by-0

High-Level Messages

- It is **subtle** to do **smoothness analysis properly** (automatically, soundly, precisely enough).
One reason: Make assumptions on target smoothness, which are easily violated.
- There are some **PL research opportunities** for **ML** (which are less explored).
This work: Static analysis for automatic planning of inference algorithms.

Thanks for your attention!

Our Approach: Soundness

Theorem Our ϕ -smoothness analysis is sound if ϕ satisfies five assumptions:

- Strictness: $\forall f = \lambda x. \perp : \mathbb{R}^n \rightarrow \mathbb{R}^m. \quad f \in \phi.$
- Projection: $\forall f = \text{proj}_{n \rightarrow m} : \mathbb{R}^n \rightarrow \mathbb{R}^m. \quad f \in \phi.$
- Restriction: $\forall f: \mathbb{R}^n \rightarrow \mathbb{R}^m, x \in \mathbb{R}^k (k \leq n). \quad f \in \phi \implies f(x, -) \in \phi.$
- Composition: $\forall f: \mathbb{R}^n \rightarrow \mathbb{R}^m, g: \mathbb{R}^m \rightarrow \mathbb{R}^l. \quad f, g \in \phi \implies (g \circ f) \in \phi.$
- Pairing: $\forall f: \mathbb{R}^n \rightarrow \mathbb{R}^m, g: \mathbb{R}^n \rightarrow \mathbb{R}^l. \quad f, g \in \phi \implies (f, g) \in \phi.$

Target smoothness property	A3 (proj.)	A4 (pair.)	A5 (rest.)	A6 (comp.)	A7 (stri.)
cont. (C^0)	○	○	○	○	○
locally Lipschitz (= $\phi^{(l)}$)	○	○	○	○	○
uniformly cont.	○	○	○	○	○
Lipschitz cont.	○	○	○	○	○
jointly diff.	○	○	○	○	○
continuously diff. (C^1)	○	○	○	○	○
smooth (C^∞)	○	○	○	○	○
real analytic (C^ω)	○	○	○	○	○
partially cont. (= $\phi^{(pc)}$)	○	○	○	✗	○
partially diff. (= $\phi^{(pd)}$)	○	○	○	✗	○
almost-everywhere cont.	○	○	✗	✗	○

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Target smoothness property	A3 (proj.)	A4 (pair.)	A5 (rest.)	A6 (comp.)	A7 (stri.)
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locally Lipschitz ($= \phi^{(l)}$)	○	○	○	○	○
uniformly cont.	○	○	○	○	○
Lipschitz cont.	○	○	○	○	○
diff. ($= \phi^{(d)}$)	○	○	○	○	○
continuously diff. (C^1)	○	○	○	○	○
smooth (C^∞)	○	○	○	○	○
real analytic (C^ω)	○	○	○	○	○
partially cont. ($= \phi^{(pc)}$)	○	○	○	✗	○
partially diff. ($= \phi^{(pd)}$)	○	○	○	✗	○
almost-everywhere cont.	○	○	✗	✗	○
almost-everywhere diff.	○	○	✗	✗	○
coordinatewise non-decreasing	○	○	○	○	○
locally bounded	○	○	○	○	○
bounded	✗	○	○	○	○
Borel measurable	○	○	○	○	○
locally integrable	○	○	✗	✗	○
integrable	✗	○	✗	✗	○

Evaluation Results

Reparameterization trick is incorrect in presence of discontinuity #2277

Open

3 tasks

fritzo opened this issue on Jan 22, 2020 · 0 comments



fritzo commented on Jan 22, 2020 · edited

Member

This issue was raised by @hongseok-yang.

In models where likelihoods discontinuously depend on a latent variable, it is incorrect to use the parameterization trick for that variable in the guide. A correct workaround is to substitute the guide distribution with a non-reparameterized copy. For example:

```
def model(data):
    z = pyro.sample("z", dist.Normal(0,1))
    p = z.round().clamp(min=0.2, max=0.8)
    pyro.sample("x", dist.Bernoulli(p), obs=tensor(0.))

def guide(data):
    loc = pyro.param("loc", torch.tensor(0.))
    scale = pyro.param("scale", torch.tensor(1.), constraint=positive)
    - pyro.sample("z", dist.Normal(loc, 1))
    + pyro.sample("z", NonreparameterizedNormal(loc, scale))
```

Assignees

No one assigned

Labels

bug usability

Projects

None yet

Milestone

No milestone

Development

No branches or pull requests