



# Proof synthesis and differential linear logic

Daniel Murfet

based on joint work with James Clift





- J. Clift and D. Murfet, *Derivatives of Turing Machines in Linear Logic*, arXiv: 1805.11813 ([gradient descent on TMs in Section 7](#)).
- J. Clift and D. Murfet, *Encodings of Turing Machines in Linear Logic*, arXiv: 1805.10770.
- J. Clift and D. Murfet, *Cofree coalgebras and differential linear logic*, Mathematical Structures in Computer Science (arXiv 2017).
- D. Murfet, *On Sweedler's cofree cocommutative coalgebra*, J. Pure and Applied Algebra, 219 (2015) 5289-5304.
- D. Murfet, *Logic and linear algebra: an introduction*, arXiv: 1407.2650.

## LINEAR LOGIC\*

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### V.5. *The exponentials*

Already in the well-known case of lambda-calculus, there are two traditions:

- the tradition of identifying the variables, which comes from beta-conversion, when we substitute  $u$  for all occurrences of  $x$ ;
- the tradition coming from the implementation, which tries to repress or control substitution.

The first tradition rests on safe logical grounds, whereas the second one is a kind of *bricolage* with hazardous justifications.

(i) As long as linear logic was resting on quantitative ideas, the principle (inspired on the way Krivine handled beta-conversion by restricting substitution to headvariables, and on the fact that a term is linear in its headvariable) suggested to use a linear 'first-order development', based on the identification between  $!A$  and  $1 + A. !A$ . The operations of identification could be seen as formal derivation or formal primitive. The interest of this approach was to propose, at the theoretical level, to replace brutal beta-conversion by iterated linear conversions.

# Linear Logic (sketch)

Types :  $A, B, C, \dots, !A, A \otimes B, A \multimap B, \dots, \underline{\text{int}}_A$  (integers),  $\underline{\text{bint}}_A$  (binary integers), ...

$\wedge \quad \Rightarrow$

Proofs :  $\underline{n} : \underline{\text{int}}_A$  (Church numerals), for  $n \geq 0$  an integer

$\underline{S} : \underline{\text{bint}}_A$  for any  $S \in \{0, 1\}^*$  e.g.  $S = 001$ .

repeat :  $! \underline{\text{bint}}_A \multimap \underline{\text{bint}}_A$

Cut-elimination is an equivalence relation on proofs

$$\begin{array}{c}
 \underline{S} \\
 \vdots \\
 \vdots \\
 \hline
 \vdash \underline{\text{bint}} \\
 \text{prom} \\
 \hline
 \vdash ! \underline{\text{bint}}
 \end{array}
 \quad
 \begin{array}{c}
 \underline{\text{repeat}} \\
 \vdots \\
 \vdots \\
 \vdots \\
 \hline
 ! \underline{\text{bint}} \vdash \underline{\text{bint}}
 \end{array}$$


---


$$\vdash \underline{\text{bint}}$$

$\sim$

$$\begin{array}{c}
 \underline{SS} \\
 \vdots \\
 \vdots \\
 \vdots \\
 \vdots \\
 \hline
 \vdash \underline{\text{bint}}
 \end{array}$$

i.e.  $\text{repeat}(S) = SS$

How does this refine the standard encodings in  $\lambda$ -calculus?





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Fundamental Study

# The differential lambda-calculus

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## Abstract

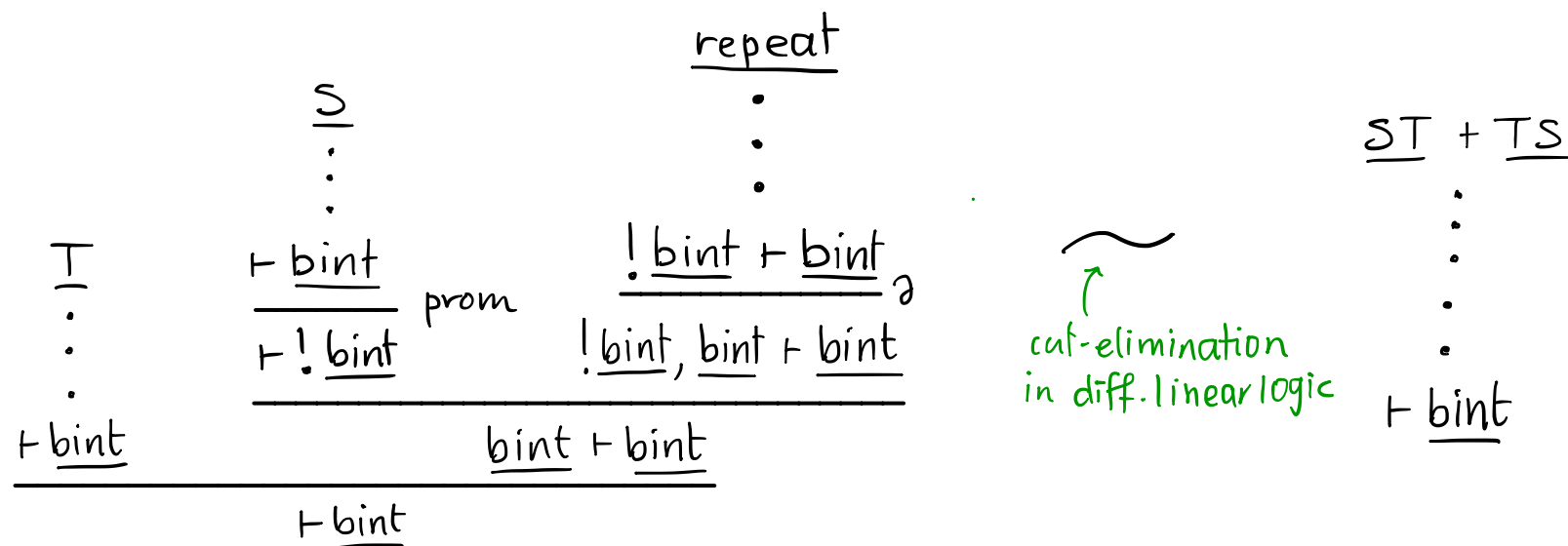
We present an extension of the lambda-calculus with differential constructions. We state and prove some basic results (confluence, strong normalization in the typed case), and also a theorem relating the usual Taylor series of analysis to the linear head reduction of lambda-calculus.

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*Keywords:* Lambda-calculus; Linear logic; Denotational semantics; Linear head reduction

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## Differential Linear Logic (sketch)



Let  $\varepsilon^2 = 0$  be an infinitesimal, then

$$\begin{aligned}
 \text{repeat}(S + \varepsilon T) &= (S + \varepsilon T)(S + \varepsilon T) \\
 &= SS + \varepsilon ST + \varepsilon TS + \varepsilon^2 TT \\
 &= SS + \varepsilon(ST + TS)
 \end{aligned}$$

Claim (Ehrhard-Regnier) The derivative of repeat at S in the direction T is ST + TS.

↑?

# Deduction rules for (intuitionistic, first-order) linear logic

$$\text{(Dereliction): } \frac{\Gamma, A, \Delta \vdash B}{\Gamma, !A, \Delta \vdash B}^{\text{der}}$$

$$\text{(Contraction): } \frac{\Gamma, !A, !A, \Delta \vdash B}{\Gamma, !A, \Delta \vdash B}^{\text{ctr}}$$

$$\text{(Weakening): } \frac{\Gamma, \Delta \vdash B}{\Gamma, !A, \Delta \vdash B}^{\text{weak}}$$

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$$\text{(Axiom): } \frac{}{A \vdash A} \quad \text{(Cut): } \frac{\Gamma \vdash A \quad \Delta', A, \Delta \vdash B}{\Delta', \Gamma, \Delta \vdash B}^{\text{cut}} \quad \text{(Promotion): } \frac{! \Gamma \vdash A}{! \Gamma \vdash !A}^{\text{prom}}$$

$$\text{(Left } \multimap \text{): } \frac{\Gamma \vdash A \quad \Delta', B, \Delta \vdash C}{\Delta', \Gamma, A \multimap B, \Delta \vdash C}^{\multimap-L} \quad \text{(Left } \otimes \text{): } \frac{\Gamma, A, B, \Delta \vdash C}{\Gamma, A \otimes B, \Delta \vdash C}^{\otimes-L}$$

$$\text{(Right } \multimap \text{): } \frac{A, \Gamma \vdash B}{\Gamma \vdash A \multimap B}^{\multimap-R} \quad \text{(Right } \otimes \text{): } \frac{\Gamma \vdash A \quad \Delta \vdash B}{\Gamma, \Delta \vdash A \otimes B}^{\otimes-R}$$



# Deduction rules for (intuitionistic, first-order) linear logic

$$\text{(Dereliction): } \frac{\Gamma, A, \Delta \vdash B}{\Gamma, !A, \Delta \vdash B} \text{ der}$$

$$\underline{001} : \mathbf{bint}_A = !(A \multimap A) \multimap (!(A \multimap A) \multimap (A \multimap A))$$

$$\text{(Contraction): } \frac{\Gamma, !A, !A, \Delta \vdash B}{\Gamma, !A, \Delta \vdash B} \text{ctr}$$

$$\text{(Weakening): } \frac{\Gamma, \Delta \vdash B}{\Gamma, !A, \Delta \vdash B} \text{ weak}$$

$$\begin{array}{c}
\frac{\overline{A \vdash A} \quad \frac{\overline{A \vdash A}}{A, A \multimap A \vdash A} \multimap L}{\overline{A \vdash A} \quad \overline{A, A \multimap A, A \multimap A \vdash A} \multimap L} \multimap L \\
\frac{}{A, A \multimap A, A \multimap A, A \multimap A \vdash A} \multimap L \\
\frac{}{A \multimap A, A \multimap A, A \multimap A \vdash A \multimap A} \multimap R \\
\frac{}{!(A \multimap A), !(A \multimap A), !(A \multimap A) \vdash A \multimap A} 3 \times \text{der} \\
\frac{}{!(A \multimap A), !(A \multimap A) \vdash A \multimap A} \text{ctr} \\
\frac{}{\vdash \mathbf{bint}_A} 2 \times \multimap R
\end{array}$$

(Axiom):  $\overline{A \vdash A}$

$$(\text{Cut}): \frac{\Gamma \vdash A \quad \Delta', A, \Delta \vdash B}{\Delta', \Gamma, \Delta \vdash B} \text{cut}$$

$$(\text{Promotion}): \frac{!\Gamma \vdash A}{!\Gamma \vdash !A} \text{prom}$$

$$(\text{Left } \multimap): \frac{\Gamma \vdash A \quad \Delta', B, \Delta \vdash C}{\Delta', \Gamma, A \multimap B, \Delta \vdash C} \multimap L$$

$$(\text{Left } \otimes): \frac{\Gamma, A, B, \Delta \vdash C}{\Gamma, A \otimes B, \Delta \vdash C} \otimes\text{-}L$$

$$(\text{Right } \multimap): \frac{A, \Gamma \vdash B}{\Gamma \vdash A \multimap B} \multimap R$$

$$(\text{Right } \otimes): \frac{\Gamma \vdash A \quad \Delta \vdash B}{\Gamma, \Delta \vdash A \otimes B} \otimes\text{-}R$$

$$\mathbf{bint}_A = !(A \multimap A) \multimap (!(A \multimap A) \multimap (A \multimap A)).$$

$$E = A \multimap A$$

$$\underline{\text{repeat}} : !\mathbf{bint}_A \multimap \mathbf{bint}_A$$

$$\begin{array}{c}
\text{comp}_A^2 \\
\vdots \\
\frac{\overline{!E \vdash !E} \quad \overline{!E \vdash !E} \quad E, E \vdash E}{\overline{!E, !E \multimap E, E \vdash E} \multimap L} \\
\frac{\overline{!E \vdash !E} \quad \overline{!E, !E \multimap E, E \vdash E} \multimap L}{\overline{!E, !E, \mathbf{bint}_A, E \vdash E} \multimap L} \\
\frac{\overline{!E \vdash !E} \quad \overline{!E, !E, \mathbf{bint}_A, E \vdash E} \multimap L}{\overline{!E, !E, !E, \mathbf{bint}_A, !E \multimap E \vdash E} \multimap L} \\
\frac{\overline{!E \vdash !E} \quad \overline{!E, !E, !E, \mathbf{bint}_A, !E \multimap E \vdash E} \multimap L}{\overline{!E, !E, !E, !E, \mathbf{bint}_A, \mathbf{bint}_A \vdash E} \text{ctr}} \\
\frac{\overline{!E, !E, !E, \mathbf{bint}_A, \mathbf{bint}_A \vdash E} \text{ctr}}{\overline{!E, !E, \mathbf{bint}_A, \mathbf{bint}_A \vdash E} \text{ctr}} \\
\frac{\overline{!E, !E, \mathbf{bint}_A, \mathbf{bint}_A \vdash E} \text{ctr}}{\overline{\mathbf{bint}_A, \mathbf{bint}_A \vdash \mathbf{bint}_A} 2\times \multimap R} \\
\frac{\overline{\mathbf{bint}_A, \mathbf{bint}_A \vdash \mathbf{bint}_A} 2\times \text{der}}{\overline{!\mathbf{bint}_A, !\mathbf{bint}_A \vdash \mathbf{bint}_A} \text{ctr}} \\
!\mathbf{bint}_A \vdash \mathbf{bint}_A
\end{array}$$

# Sweedler semantics

$\llbracket - \rrbracket : \mathcal{LL} \longrightarrow \text{Vect}_k$   
 ( $k$  an algebraically closed field)

$$\llbracket A \multimap B \rrbracket = \text{Hom}_k(\llbracket A \rrbracket, \llbracket B \rrbracket)$$

If  $\dim \llbracket A \rrbracket = m$ ,  $\dim \llbracket B \rrbracket = n$   
 this is the space of  $n \times m$  matrices.

$$\llbracket A \otimes B \rrbracket = \llbracket A \rrbracket \otimes \llbracket B \rrbracket$$

Dimension  $mn$ , spanned by a  
 basis  $u_i \otimes v_j$  where  $(u_i)_{i=1}^m$ ,  
 $(v_j)_{j=1}^n$  are bases for  $\llbracket A \rrbracket, \llbracket B \rrbracket$ .

$$\llbracket !A \rrbracket = \bigoplus_{P \in \llbracket A \rrbracket} \text{Sym}(\llbracket A \rrbracket)$$

Cofree cocommutative coalgebra over  $\llbracket A \rrbracket$ ,  
 studied by Sweedler.

Cut = composition  
 Contraction = comultiplication  
 Weakening = counit

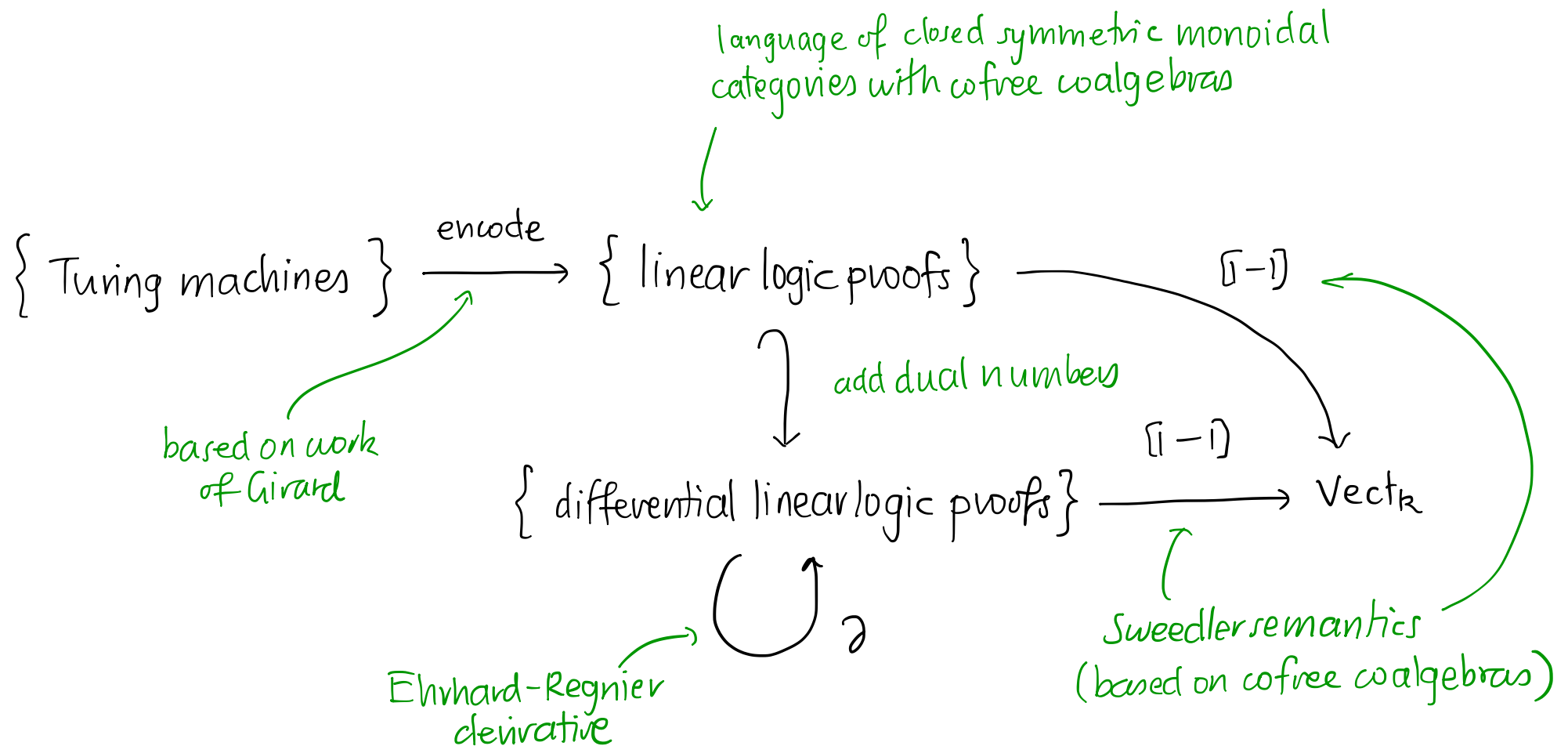
$$\left[ \begin{array}{c} \pi \\ \vdots \\ \frac{!T \vdash A}{!T \vdash !A} \text{prom} \end{array} \right] = \text{unique morphism of coalgebras } \mathcal{J} \text{ making the diagram below commute}$$

$$\begin{array}{ccc} \llbracket !T \rrbracket & \xrightarrow{\mathcal{J}} & \llbracket !A \rrbracket \\ & \searrow [\pi] & \downarrow \text{universal} \\ & & \llbracket A \rrbracket \end{array}$$

(see "Cofree coalgebras and differential LL")



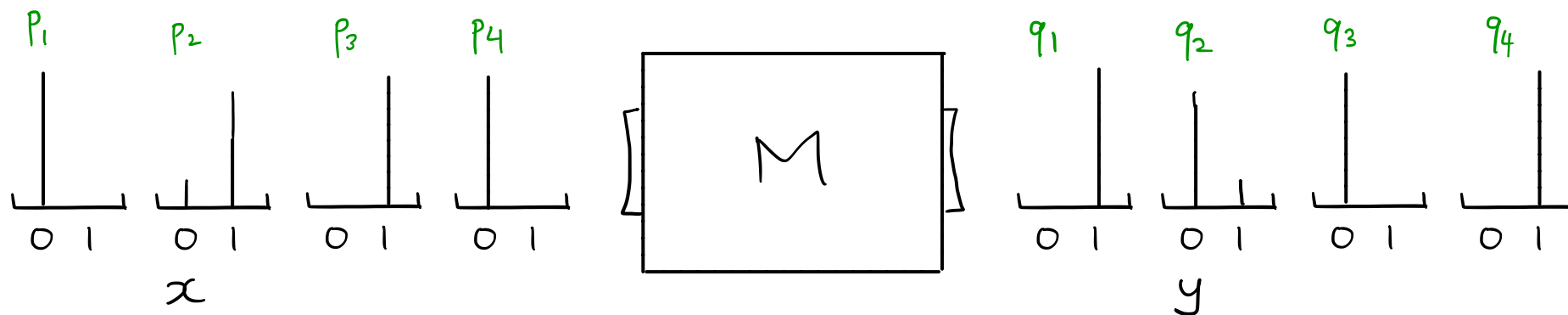
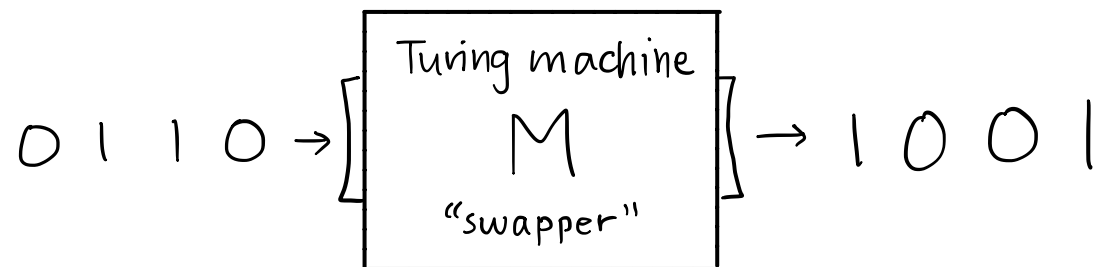
# Differentiating Turing Machines



QUESTION : What does the derivative of a Turing Machine compute?

# Differentiating Turing Machines

How to make infinitesimal changes to discrete inputs?



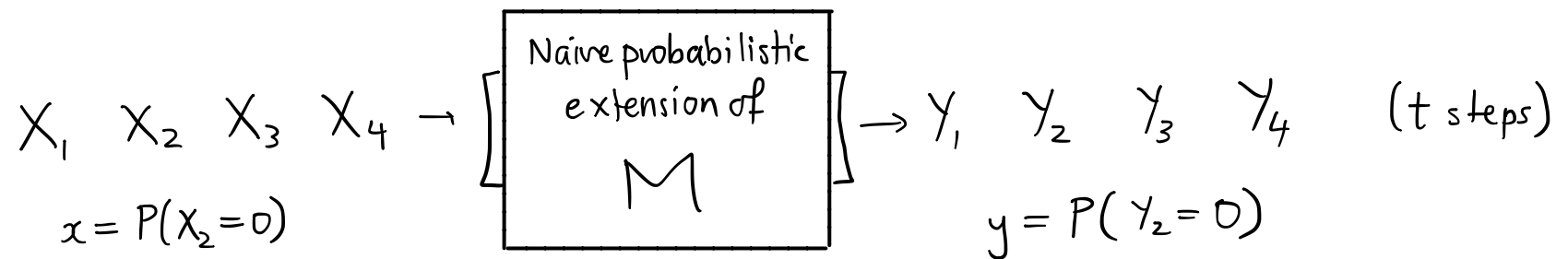
$$\left. \frac{\partial y}{\partial x} \right|_{x=0} = \left. \frac{\partial}{\partial x} (1-x) \right|_{x=0} = -1$$

If we propagate uncertainty using standard probability, answers are independent of the algorithm and therefore meaningless.

## Differentiating Turing Machines

How to propagate uncertainty through an algorithm?

Use the Sweedler semantics!



$\left. \frac{\partial y}{\partial x} \right|_{x=0}$  is computed by the Ehrhard-Regnier derivative of the  $t$ -step function of the encoding of  $M$ .

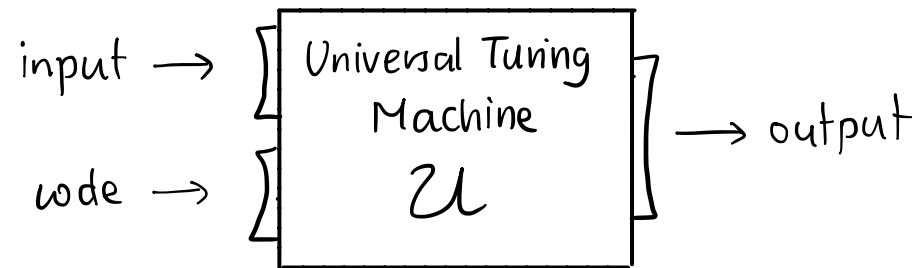
QUESTION : What does the derivative of a Turing Machine compute?

ANSWER : Rates of change of naive probability.



## Proof Synthesis / TM synthesis

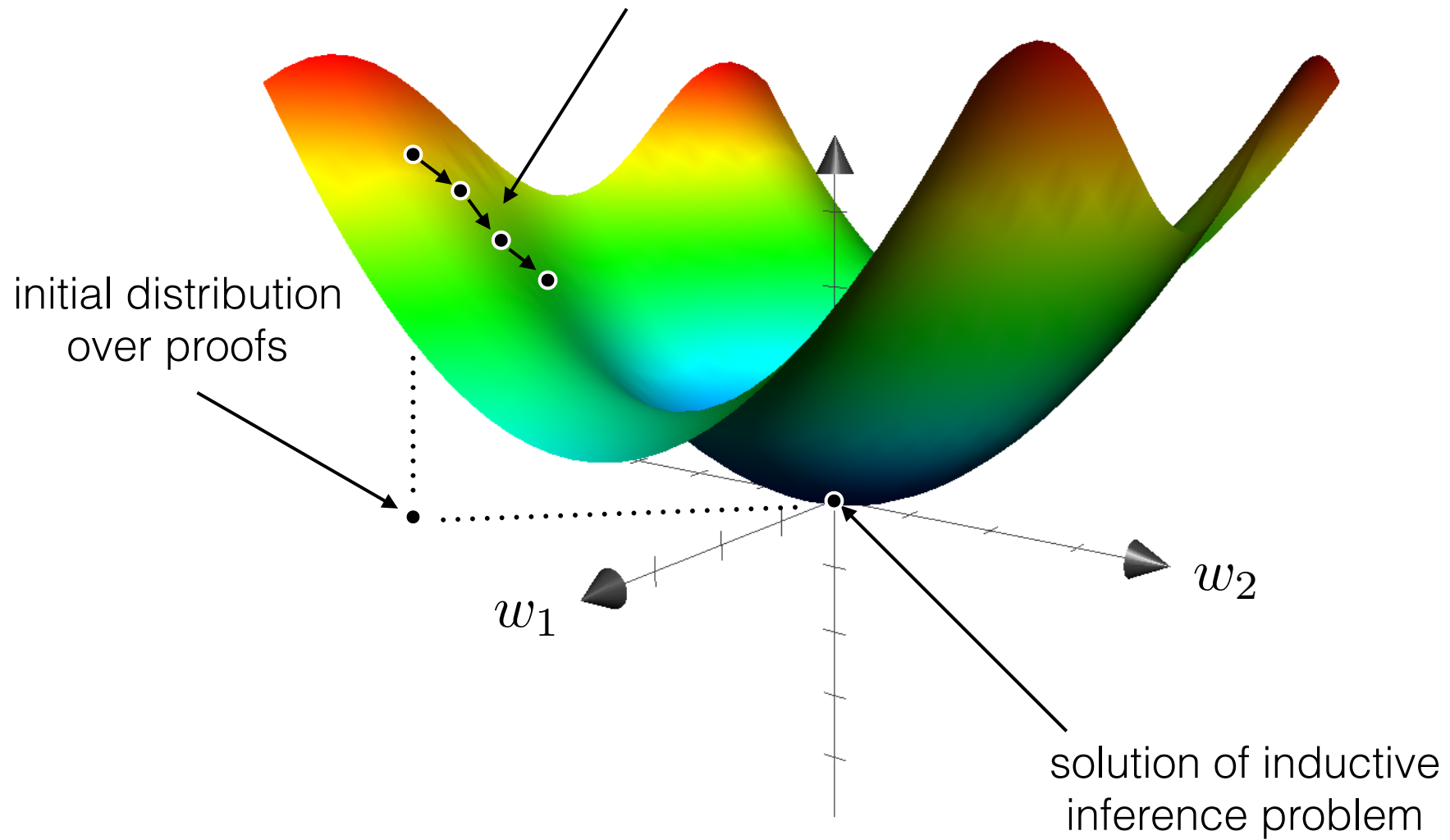
PROBLEM Given  $u:A$  and  $v:B$  find  $\pi : !A \multimap B$  s.t.  $\pi(u) = v$ .  
(usually for multiple pairs, subject to "regularisation" i.e. simplicity of  $\pi$ )



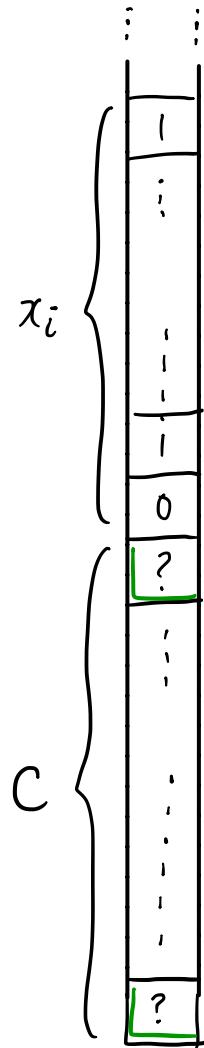
Tuning Machine synthesis by gradient descent :

┌ Vary distributions over code bits  $\in [0, 1]^N$  to minimise  
a smooth loss function  $L : [0, 1]^N \longrightarrow \mathbb{R}$ .  
└

gradient descent using Ehrhard-Regnier derivatives



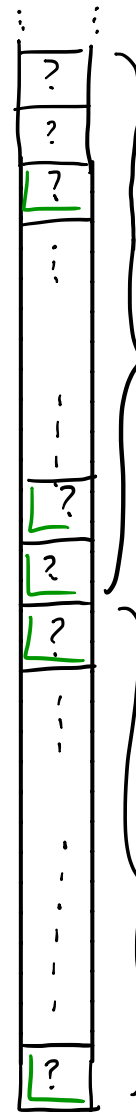
UTM tape



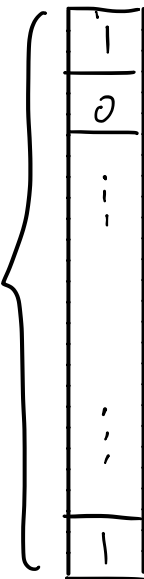
naive probabilistic extension of UTM  $u$

$\Delta \text{step}_u^{t_i}$

$t_i$  timesteps of UTM evolution



KL  
KL  
:  
predicted tape contents  $y_i$   
 $p_i$  (a sequence of distributions)  
KL

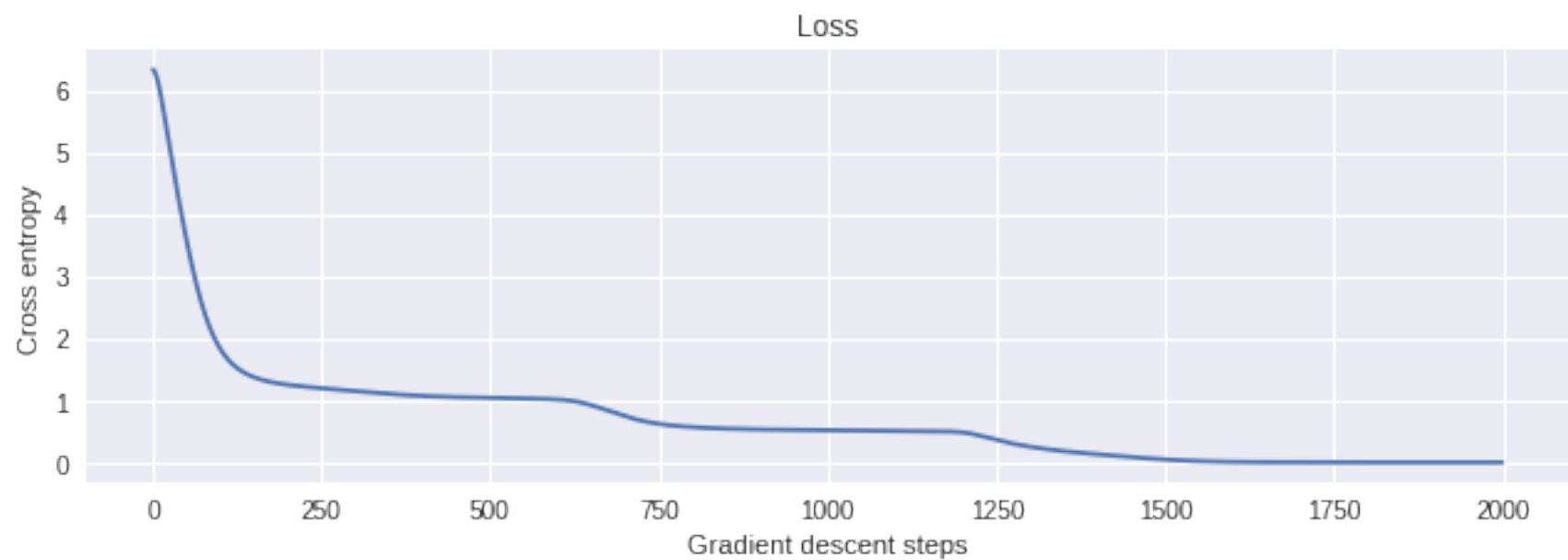
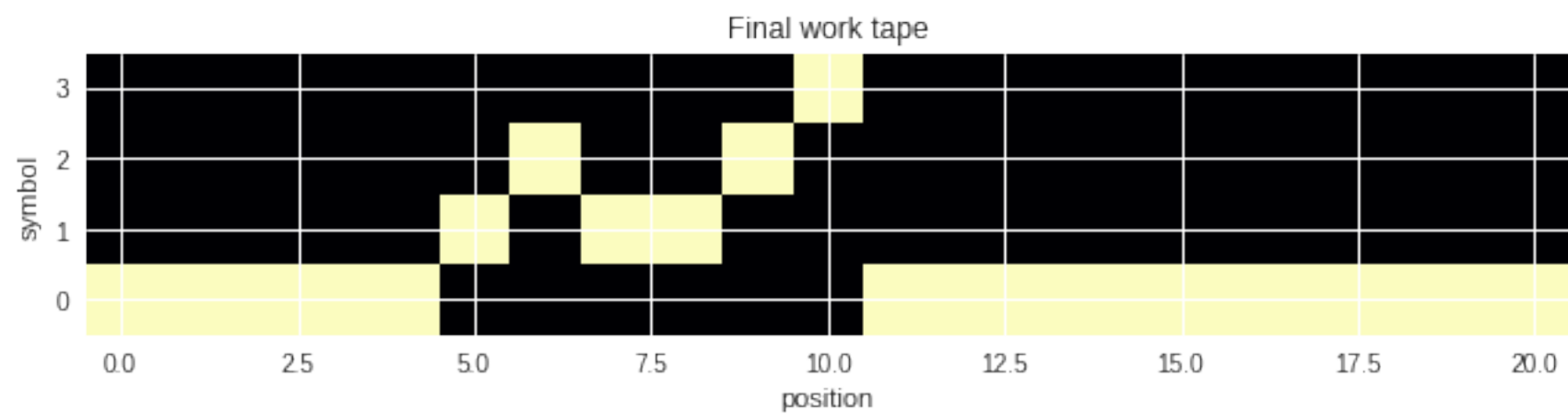


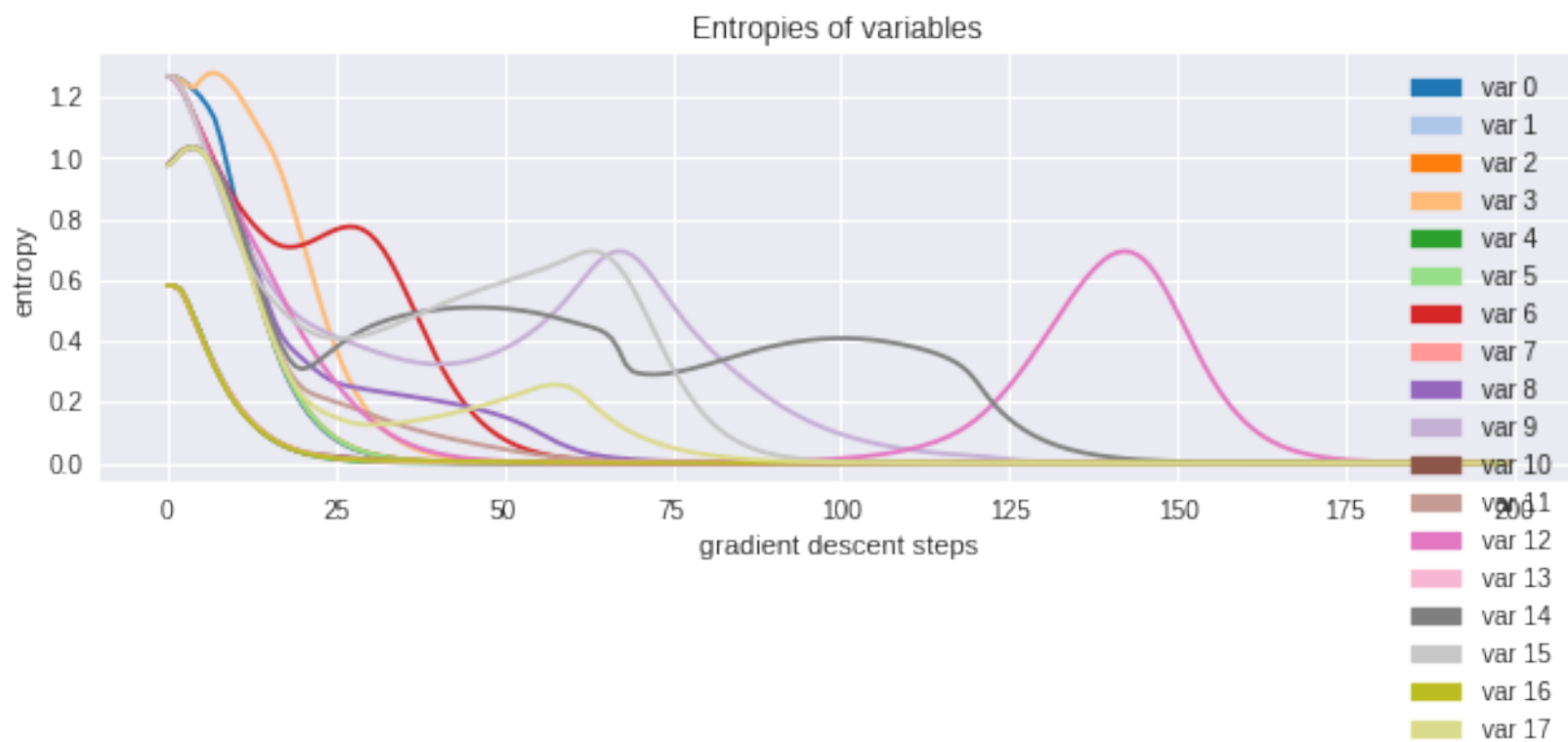
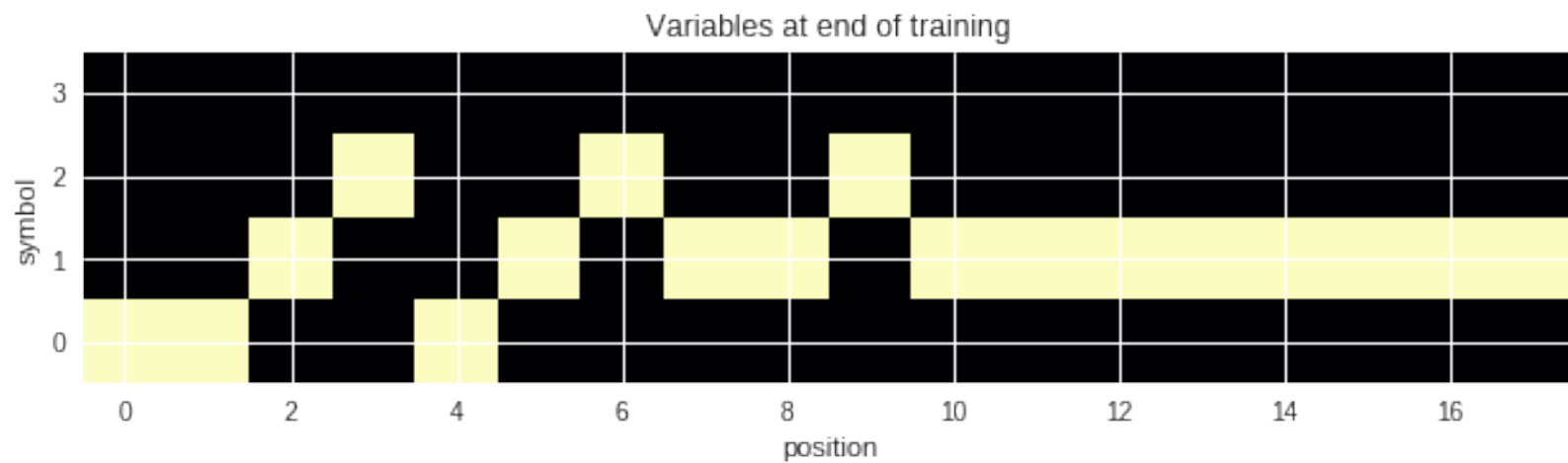
$$L(C) = \sum_{i=1}^N D_{KL}(y_i \parallel p_i) + \dots$$

$$D_{KL}(q \parallel p) = \sum_{i \in \{0,1\}} q_i \ln(q_i/p_i)$$

$p, q$  distributions on  $\{0,1\}$ .







- Synthesis by gradient descent works in toy examples, but is unlikely to work in nontrivial examples ( explosion of local minima, it seems Occam's razor is not a sufficiently strong prior in the continuous regime ).
- Similar methods of propagating uncertainty through algorithms have arisen (in an ad hoc way) in the machine learning literature :
  - (DeepMind) R. Evans, E. Grefenstette "Learning explanatory rules from noisy data" Journal of AI Research 61 (2018) 1-64.
  - (Microsoft) A. Gaunt et. al "TerpreT: a probabilistic programming language for program induction" 2016.

## CONCLUSION

- ① Proofs in linear logic admit a derivative (Ehrhard-Regnier)
- ② These derivatives compute (for certain proofs) rates of change of naive probability (Clift-M).
- ③ One can do proof synthesis by gradient descent, using loss functions defined on spaces of distributions over proofs (although this is not currently practical!).

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