

Part I

THE SHOWCASE

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INTRODUCTION

Probability has compelled beyond all alternatives as a representation of knowledge in domains rife with uncertainty; and probabilistic inference correspondingly so as a method for reasoning. The success story is only partially written however; while Bayes' Rule states how we should update our beliefs in hypotheses conditioned on evidence, it tells us only declaratively, and leaves us with no indication of such. In a sense we have been provided with the logic.

The majority of current these models explain how learners select among competing hypotheses; for the most part, they do not attempt to explain how learners construct hypotheses in the first place. Hypothesis. However, efficiently sampling hypotheses is not the same as constructing them.

Perhaps. However, with only the minimal constraints of simplicity, grammaticality, and previously productive templates, changes to hypotheses generated by random variation seems at best inefficient. More importantly, our minds seem to have access to rich sources of information that could better constrain the process of hypothesis generation and that current approaches do not exploit.

Build on upon recently interpretations of inference in computational terms, I am to incorporate conditions constructively into generative models. That is, given a generative model manifested as a stochastic *prior program* P , and a conditioning predicate C we wish to construct a new program P^* which samples only values which adhere to our constraints and remains. The approach here attempts to concretise many of the concepts outlined in [?] , and perhaps suprisingly, we draw more from the fields of program semantics.

The feasibility of this aim is vulnerable; if it were possible to Consider the ease with which you can compose a paragraph that rhymes, generate a polynomial expression, draw a graph without cycles. From a probabilistic inference perspective, each of these examples can be considered a generative model compared with a condition, and our ability to perform such tasks is probabilistic inference.

A further appeal of such as approach is its potential to bridge between discriminative and generative approaches Discriminative models may detect broad level characteristics of a scene, while generative use these as constraints.

First we will summarise QUERY, then outline many approaches

1.0.1 Query

QUERY is a formalism of probabilistic inference stated explicitly in computational terms; our explanation is stated in terms of models of computation. Developed first as a primitive function in the probabilistic programming language Church [?], elaborated on in [?].

LAMBDA CALCULUS INTERPRETATION In [?], query is formulated as a probabilistic turing machine (PTM), which takes two inputs, a prior program P and a conditioning predicate C . Both P and C are themselves encodings of PTMs that take no input. QUERY generates a sample from P . Then, if X is satisfied, then this sample is outputted, otherwise the process is repeated.

```
(define (query exp pred)
  (let ((val (eval exp)))
    (if (pred val)
        val
        (query exp pred))))
```

1.0.2 Constrain

The semantics of CONSTRAIN can be readily understood in terms of QUERY. If we take the above lambda-calculus definition of query, as a function, CONSTRAIN can be viewed simply as query with all its arguments partially evaluated.

```
(define (constrain exp pred)
  (fn [] ))
```

Simply put, query returns a sample given a model and condition, while constrain given the same input returns a function of no arguments which calls query.

The difference can be seen as the difference from sampling $P(x|C)$ or constructing a new prior $P^*(x)$.

This alone is not a large step, what is important is to retain that condition C

1.0.3 Distribution Conserving

Note: The content of this chapter is just some dummy text.

Distribution preserving or not How to deal with constraints

CONSTRAINED GENERATIVE MODELS

There are a number of ways to explore this problems, varying principally in domain specificity, declarativeness of specification.

2.1 TRANSFORM NAIVE GENERATIVE MODEL

Transformational Programming is a prominent method used in automated program development. A formal, declarative specification of a program is *refined* into a complete program by applying a sequence of correctness-preserving transformations. We can appropriate this framework for our purposes; transform a naive generative into a semantically equivalent (and hence distribution equivalent) program.

From a stochastic program P and constraint C , we construct a new program R_P^C with rejection sampling semantics. R_P^C executes P to sample from its prior and returns the sample C is satisfied, otherwise a further attempt is made. Formally we can describe R_P^C as a partially-evaluated higher order function, in lisp notation:

```
(defn R [P C]
  (let [sample (P)]
    (if (true? (C sample))
        sample
        (R P C))))
```

Partial evaluation of a program means to take some subset of its arguments, and compile a new program with this subset fixed (under closure) and no longer arguments.

Our next objective is to perform a series of transformations to improve the efficiency R_P^C . By constraining this set of transformations to be semantic preserving; that is any new program.

2.1.1 Domain specificity

2.1.2 Domain specificity

2.2 ERROR CORRECTING EVALUATION

Dependencies on domain specific knowledge is problematic. Representing The alternative seems even more implausible; how can one generate only convex polygons without any understanding of convexity, and more generally geometry.

The approach described here takes a middle ground to circumvent an ostensible requirement for domain specific knowledge. First, by treating our conditions as computable functions, predicates themselves contain a wealth of information, which may be sufficient. The

idea is to not treat these predicates as black boxes, but instead to analyse their structure. Second structured objects can be decomposed into parts, and unsatisfiability can be *blamed* on subcomponenets. We can fix a In other words, neither our predicates nor objects upon which predicates are applied are monolithic, impenetrable black boxes

2.2.1 *Program Transparency*

TODO EXPLAIN PROGRAM TRANSPARENCY BOTH INFORMALLY AND ATTEMPT A FORMAL DEFINITION

2.2.2 *Blame attribution*

The approach outlined here has for the moment at least been namde error correcting evaluation. This is because the process is derived from program evaluation, or interpretation. The general goal is to evaluate our condition C find the causes of unsatisfiability, that is, attribute blame for our to some portion of the code. Then, we seek to figure out alternative words (execution traces), that would cause this unsatisfiability to become satisfied.

2.2.3 *Unification: Attribution blame to the generative model*

The

Filter generative model

. From D derive a *filter function* f which transforms a sample from a naive model to one which satisfies D. That is $f : O \rightarrow O^*$, where $\bigwedge_i d_i(o^*) = 1$. Examples of f could be convex hull algorithms, cycle removing, or variable separation. Although in both this and the first approach we seek a sample which satisfies D, there are important differences. Here we do not reformulate the problem in optimisation terms, and seek a transform which will directly result in our constraints being satisfied. Clearly, as exemplified

Questions What if all the constraints can't be satisfied, do we want partial satisfaction, do we want to know?

CASE STUDY

Either 1. Polygon example 2.

3.1 OPTIMISE INITIAL SAMPLE

. Preliminary evidence has suggested that choosing a good initial sample has convergence advantages. Both inference and search methods begin with an initial sample or configuration, sampled from the prior distribution or chosen arbitrarily. The idea here is to optimise this initial sample such that it adheres to our set of constraints. Formally our objective in search is given some configuration space X , and a cost function $f : X \rightarrow \mathbb{R}$, our objective is to find $\operatorname{argmin}_x f$. In inference terms we would like to sample from a posterior distribution $P(X|Y)$.

Additionally, given a set of declarative constraints D where $d \in D : X \rightarrow \{0, 1\}$, we wish to find an initial sample or configuration $o_0 \in O$, which minimises some function $g(d_1(o_0), \dots, d_n(o_0))$. g is required to balance multiple constraints and a simple example could be $g(p_1, \dots, p_n) = \sum_i 1 - p_i$.

Domain general. Unsure how useful this? Will need to test If I just want a new gen model, not doign inference, I could optimise every sample, but then my new distribution would be dependent on my optimisation dynamics. Choice is g is rather arbitrary How to do the optiisation?

3.1.1 *Autem Timeam*

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3.2 ANOTHER SECTION IN THIS CHAPTER

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DESCRIPTION-LABEL TEST: Pellentesque habitant morbi tristique senectus et netus et malesuada fames ac turpis egestas. Donec odio elit, dictum in, hendrerit sit amet, egestas sed, leo. Praesent feugiat sapien aliquet odio. Integer vitae justo. Aliquam vestibulum fringilla lorem. Sed neque lectus, consectetur at, consectetur sed, eleifend ac, lectus. Nulla facilisi. Pellentesque eget lectus. Proin eu metus. Sed porttitor. In hac habitasse platea dictumst. Suspendisse eu lectus. Ut mi mi, lacinia sit amet, placerat et, mollis vitae, dui. Sed ante tellus, tristique ut, iaculis eu, malesuada ac, dui. Mauris nibh leo, facilisis non, adipiscing quis, ultrices a, dui.

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This statement requires citation ? [?].

¹ De web nostre historia angloromanic.

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Table 1: Autem timeam deleniti usu id. ?

3.2.1 *Personas Initialmente*

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A. Enumeration with small caps

B. Second item

Another statement requiring citation ? [?] but this time with text after the citation.

3.2.2 *Figure Citations*

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o, facite linguistic registrate se nos. Gymnasios, e. g., sanctificate sia le, publicate [Figure 1](#) methodicamente e qui.

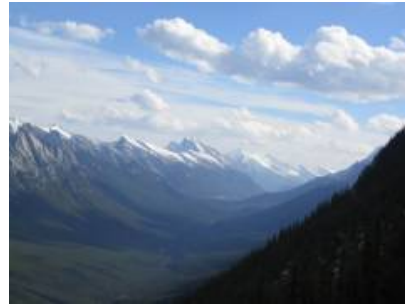
Lo sed apprende instruite. Que altere responder su, pan ma, i. e., signo studio. [Figure 1b](#) Instruite preparation le duo, asia altere tentation web su. Via unic facto rapide de, iste questiones methodicamente o uno, nos al.



(a) Asia personas duo.



(b) Pan ma signo.



(c) Methodicamente o uno.



(d) Titulo debitas.

Figure 1: Tu duo titulo debitas latente.