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Exploring Visual Programming Concepts for Probabilistic Programming Languages

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Abbreviations

ADT	Abstract Data Type
DARPA	Defense Advanced Research Projects Agency
ML	Machine Learning
IDE	Integrated Development Environment
PP	Probabilistic Programming
PPAML	Probabilistic Programming for Advancing Machine Learning
PPL	Probabilistic Programming Language
PR	Probabilistic Reasoning
PVL	Purely Visual Language
VP	Visual Programming
VPE	Visual Programming Environment
VPL	Visual Programming Language

Chapter 1

Introduction

This first chapter aims to provide the reader with an overview of this dissertation. It starts by introducing the context this work is inserted in, identifying the problem which we aim to solve, how we plan on solving it, and the expected outcome. Lastly, it gives a bird's eye view of this report's structure.

1.1 Context

There is, among several domains with interesting and relevant problems to solve (computer vision [KT15], cryptography, biology, fraud detection, recommender systems [Alp10], . . .), the recurring necessity to be able to make decisions in the face of uncertainty using machine learning (ML) methods.

Successful ML applications include Google's personalized advertising and context-driven information retrieval, Facebook's studies of how information spreads across a network or UC Berkeley's AMPLab contributions towards Amazon Web Service and SAP's products [BAF+15].

Typically, there are two alternatives for solving this class of problems: either use an existing machine learning model (such as KNN, neural networks or similar) [Sch08] and try to fit your data into the model, or build a probabilistic model for your own particular problem so you can better leverage domain knowledge [Gri13].

In the second alternativa one common way to approach it is by using bayesian reasoning, where you model unknown causes with random variables, feed the model the data you have gathered and then perform inference to query for the desired, and previously unknown, variables [Dow12]. The problem in choosing this method is this last step, since it is non-trivial to write an inference method [DL].

The solution to this has been building generic inference engines for graphical models, so that modeling and inference can be treated as separate concerns and people can focus on the modeling [JW96]. However, not all models can be represented as graphical models, and that's why we now

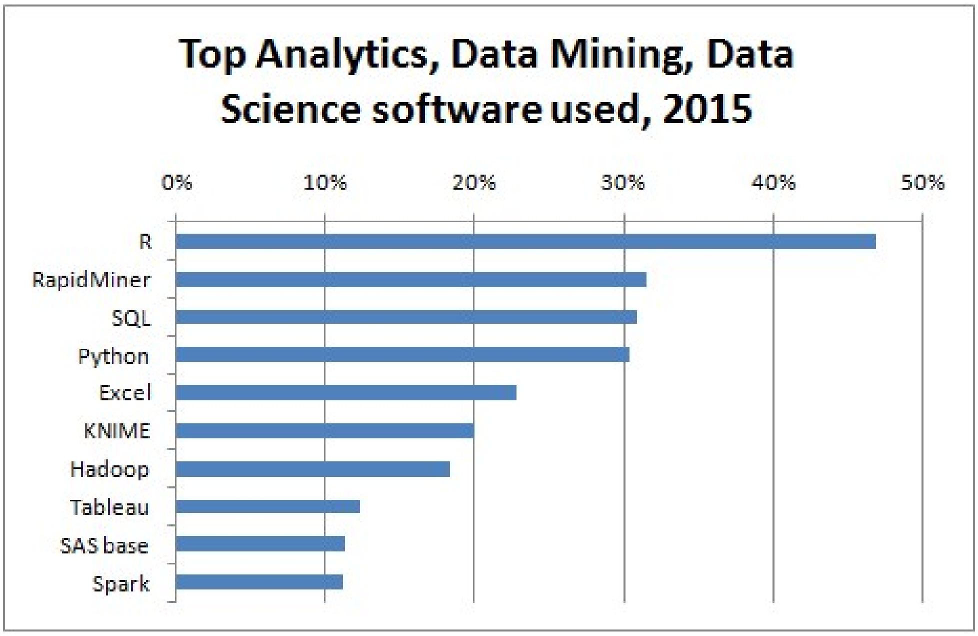


Figure 1.1: Top 10 Analytics Tools [Pia15]

have Probabilistic Programming Languages (PPLs). Probabilistic Programs let you write your model as a program and have off-the-shelf inference [Pre03].

1.2 Problem

In spite of these examples of applications in the industry, ML has been identified by Gartner, in its Hype Cycle annual review, to be in the "Peak of Inflated Expectations" stage, still far from the "Plateau of Producitvity" [Sta15].

It has also been said that ML's applications are rarely seen outside the academia, with Wagstaff claiming that there is a "frequent lack of connection between machine learning research and the larger world of scientific inquiry and humanity" [Wag12].

Arguably the scenario is even worse for PPLs, having even less adoption among tech companies than other ML methods, such as neural networks or other supervised learning models. One factor which may be contributing to this lack of usage, despite PP's power and flexibility, is the difficulty for data scientists to adapt to the textual interface these languages provide, which lack the graphical intuiton provided by other tools they are accustomed to. In a poll made to find out the most popular data-mining tools among data scientists (see Figure 1.1), half of the top 10 tools are graphically-interactable.

1.3 Motivation and Goals

The Defense Advanced Research Projects Agency (DARPA), one of the funders behind PPLs' research, has recognized some of the problems identified by Wagstaff and started a program called Probabilistic Programming for Advancing Machine Learning (PPAML) to address the shortcomings of current ML methods [Jag13]. It identifies five strategic goals:

- Shorten machine learning model code to make models faster to write and easier to understand
- Reduce development time and cost to encourage experimentation
- Facilitate the construction of more sophisticated models that incorporate rich domain knowledge and separate queries from underlying code
- Reduce the level of expertise necessary to build machine learning applications
- Support the construction of integrated models across a wide variety of domains and tool types

The purpose of this work is to try addressing the first four. In order to do so we aim to overcome the difficulties in learning a new language, either for unexperienced developers or seasoned ones, such as learning yet another syntax or getting accostumed to the language's idioms. It is known that typical languages are difficult to learn and use [LO87a] and that there are advantages in providing a language with a visual interface [AA92]. Also, studies have shown that programmers and data scientists alike resort to mental imagery when solving problems [Das02][PB99], so by providing such an interface we can approximate how people think and how they use the language to solve the problem at hand.

So, the goal of this dissertation will be to develop a Visual Programming Language (VPL) with probabilitics programming capabilities. The targeted audience are programmers and data scientists with background knowledge in statistics who aren't still comfortable with full blown PPLs, but wish to educate themselves in the topic so they can eventually leverage the power of this novel machine learning approach.

The way to do so would be developing a graphical node-based editor, similar to RapidMiner or Blender Composite Nodes, but that runs in the browser. The given editor would have the capability to compile its graph to the textual representation in the target PPL so that the user can run what he has designed, either as a standalone script or even by integrating it with his existing projects.

The hypothesis under consideration is this graphical representation is more intuitive and easy to learn that a full-blown PPL. We intend to validate such hypothesis by ensuring that classical problems solved in the literature by PPLs are also supported by our graphical representation, and then measure how quickly a group of people trained in statistics would produce a viable model in both alternatives.

1.4 Outline

Para além da introdução, esta dissertação contém mais x capítulos. No capítulo 2, é descrito o estado da arte e são apresentados trabalhos relacionados. No capítulo 3, ipsum dolor sit amet, consectetuer adipiscing elit. No capítulo 4 praesent sit amet sem. No capítulo 5 posuere, ante non tristique consectetuer, dui elit scelerisque augue, eu vehicula nibh nisi ac est.

Chapter 2

Background & State of the Art

This chapter has two purposes: describing the foundations on which this work is built on, namely Machine Learning (ML), Probabilistic Reasoning (PR), Prograbilistic Programming (PP) and Visual Programming(VP) while enumerating different tools which are based on one of these concepts.

2.1 Machine learning

Machine learning (ML) is a field which can be seen as a subfield of artifical intelligence that incorporates mathematics and statistics and is concerned with conceiving algorithms that learn autonomously, that is, without human interventation [Bri16][Sch08]. It has the potential to impact a wide spectrum of different areas such as biology, medicine, finance, astronomy [Ama13], computer vision, sales forecast, robotics [Alp10], product recommendations, fraud detection or internet ads bidding [Gri13].

Learning from data is commercially and scientifically important. ML consists of methods that automatically extract interesting knowledge in databases of sometimes chaotic and redundant information. ML is a data-based knowledge-discovering process that has the potential not only to analyze events in retrospect but also to predict future events or important alterations [Geo16].

2.2 Probabilistic Reasoning

Probabilistic reasoning (PR) is the formation of probability judgments and of subjective beliefs about the likelihoods of outcomes and the frequencies of events [?], it is a way to combine our knowledge of a situation with the laws of probability. There are subjective belifs because, in non-trivial decision-making there are unobserved factors that are critical to the decision in conjunction with several sources of uncertainty [GSD], such as:

- Uncertain inputs, due to missing or noisy data

- Uncertain knowledge, where multiple causes lead to multiple effects, or there is an incomplete knowledge of conditions, effects and causality of the domain or simply because the effects are inherently stochastic.

So, probabilistic reasoning only gives probabilistic results.

It is one way to overcome cognitive bias and be able to make rational decisions [SG01]. A trial has been made [CSB82] where physicians were asked to estimate the probability that a woman with a positive mammogram actually has breast cancer, given a base rate of 1% for breast cancer, a hit rate of about 80%, and a false-alarm rate of about 10%. It reported that 95 of 100 physicians estimated the probability that she actually has breast cancer to be between 70% and 80%, whereas Bayes's rule gives a value of about 7.5%. Such systematic deviations from Bayesian reasoning have been called "cognitive illusions,". We will describe both Bayes's rules and Bayesian reasoning in the next section.

2.2.1 Bayesian Reasoning

One way to approach PR is by using bayesian reasoning, which is inspired in the Bayes Theorem (or Rule, or Law). An equivalent formula to the theorem, in its simplest form (applied to a single event) is:

$$P(A \mid B) = \frac{P(A \wedge B)}{P(B)}$$

Where P(A|B) defines the probability of event A given that B occurred. The theorem defines how hidden causes (A) relate to observed events (B), given a causality model (P(A, B) or P(B|A)*P(A)) and our knowledge of the probability of the occurrence of events (P(B)). The inverse is also true, as we will see further ahead in this section. As an example, P(penalty | goal) defines the probability that a penalty kick was scored, knowing that there was a goal.

There are at least two interpretations to the theorem and regarding how one may think about its results [Fie06]:

- Frequentist interpreation: probabilities are defined by the relative frequency of events, given a natural sampling. Meaning, the probabiltiy of obtaining 'Heads' when rolling a dice is equal to the number of 'Heads' obtained after rolling the dice a sufficient number of times relative to the total number of times the dice has been rolled.

- Epistemological interpreation: probabilities represent a measure of belief. It can either be a result logical combination of probabilities through the usage of axioms (it's closely related to Aristotlean logic) or it can also reflect a personal belief (which is called a subjective view).

Table 2.1: Alarm system confusion matrix

	alarm	$\neg alarm$
burglary	0.09	0.01
$\neg burglary$	0.1	0.8

2.2.1.1 An example

One example of the application of this theorem is [GSD]: you know your home's alarm is ringing, but you don't know whether that was caused by a burglar or something else (maybe a bird triggered it, or there was a malfunction in the alarm system). How confident are you that you're being robbed? Consider that the alarm company, based on quality trials, defined in the confusion matrix for P(alarm, burglary) (Table 2.1).

You can interpret each table's cell as P(A, B). For instances, the top left cell is the probability that the alarm rings and there is a burglar, while the bottom left cell is the probability that the alarm rang but there was no burglar (a false positive).

If we substitute the values of Bayes' rule described above, we get:

$$P(burglar \mid alarm) = \frac{P(burglar, alarm)}{P(alarm)}$$

Where results is 0.09 / 0.19 = 0.47. So, even if the alarm is ringing, there is just a 47% probability that the house is actually being robbed.

The previous example illustrates the simplest case of applied BR, but it is also possible to combine several variables. One way to represent this kind of scenario is by expressing the variables in a directed acyclic graph, where the relation "Parent" stands for "May cause" and you can specify the conditional probabilities of a child given a parent's result. This graphical model is called a Bayesian Network.

2.2.1.2 Bayesian Networks

We can extended our alarm example further, by considering not only a burglar can trigger the alarm, but an earthquake also can (while there can still be false positives). Also, consider that we have 2 neighbors (Mary and John) who may call us whether the alarm is ringing or not. This problem is represented in figure **??**.

Some interesting question we can ask, given this scenario are:

If John calls saying the alarm is ringing but Mary doesn't, what are the odds it really is ringing?

If the alarm is ringing, was there an earthquake?

What are the chances that both my neighbors call, the alarm is ringing, but there is neither a burglary nor an earthquake?

This last example, for instances, would be calculated as: P(J, M, A, $\neg B, \neg E) = P(J|A) * P(M|A) * P(A|\neg B, \neg E) * P(\neg B) * P(\neg E) = 0.9 * 0.7 * 0.001 * 0.999 * 0.998 = 0.00062$.

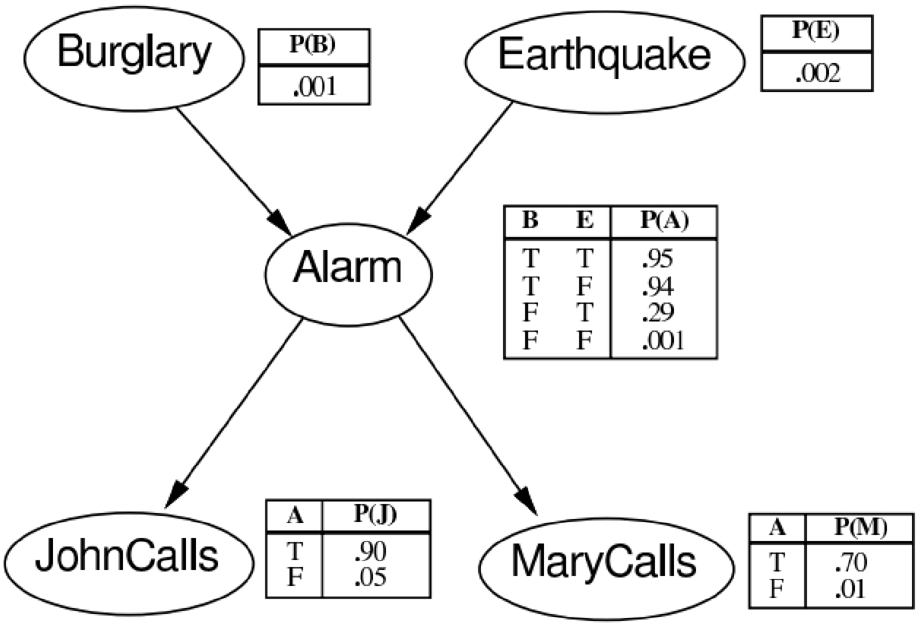


Figure 2.1: Belief network for the alarm problem [Wan02]

Notice how counter-intuitive this example is: the probability of there being an earthquake is about 32 times larger then there being an earthquake, the alarm ringing and the neighbors calling us, even if the conditional probabilities are reasonably high (0.95, 0.9 and 0.7). This is the result of the calculation of the joint probability being an highly combinatorial problem, which is yet another argument in favor of using PR rather than subjective heuristics.

2.2.1.3 Bayes' and data streams

In practical ML applications, it is often the case that there is an incoming stream of new data, rather than one-time batch calculations. BR can accomodate this way of thinking, which A. Downey called diachronic interpretation [Dow12], where diachronic means that something is happening over time (in this case the probability of the hypotheses, as new data arrives). In order to make sense of this definition, we may rewrite Bayes' rule as:

$$P(H \mid D) = \frac{P(D \mid H)\,P(H)}{P(D)}$$

Where:

- H: hypothesis
- D: data
- p(H): probability of the hypothesis before the new data is taken into account. Also called **prior**. It can either be calculated using background information or subjectively defined using

domain knowledge. Loses significance as new data is added, so its choice is not determinant to the model's performance in the long run.

- p(H|D): what we want to calculate, the probability of the hypothesis after considering the new date. It is called **posterior**.
- p(D|H): probability of the data if the hypothesis was true, called the **likelihood**.
- p(D): probability of the data under any hypothesis, called the **normalizing constant**.

Under this interpretation, you may continuously feed data into the model and see the probabilities getting updated. We will see more practical examples of this in section 2.2.2.

2.2.1.4 Beyond Bayesian Graphical Model

At first glance, someone who is learning for the first time about PR applied to ML, may think that graphical models such as the one presented in Figure 2.1 are the best there can be done in terms of using a graphical interface for solving this kind of problems and that the only thing is missing is an automated way to make the calculations.

While it is true we have never refered mentioned techniques or tools that automatically do inference over a Bayesian Network, there are several tools with that capability (including an R package [øjsgaard2013] or standalone tools [Res10]).

However, not all PR can be done via Bayesian Networks and not all graphical models are enough for complete PR [DL13]. PP are the largest class of models available, and there are also more algorithms for inference than just the calculation of joint probabilities (like we did in the alarm example), as we will discuss in Section 2.2.2.

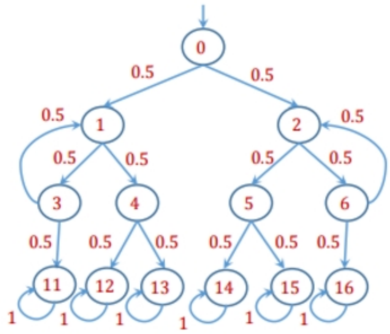
Bayesian Networks are not the only kind of graphical model. Another one would be Markov Chains, which is yet another example of a model which is not able to represent all PR problems. This is clear when we realize that, while PPLs support a large number of different distributions (such as Normal, Laplace, Gamma, Half-Cauchy or *t*), all Bayesian Networks and Markov Chain can be represented in a PPL by just using Bernoulli distributions [Gor14]. We can see an example of such a translation in Figure 2.2.

<—– rever com base em prob inference for graphical models

2.2.2 Probabilistic Programming Languages

2.2.2.1 The Probabilistic Program-Model duality

A probabilistic program (PP) is an ordinary program (that can be written in mainstream languages such as C, Java or Haskell) whose purpose is to specify a probability distribution of its variables. This is done by sampling over several executions of the program. The only needed construct the language has to support, in order to be able to write a PP, is having a random number generator [DL]. This whole concept couldn't be better explained than in this text by Freer and Roy, regarding Church (a PPL, which we describe in Section 2.4.3) but common to any PP:




```
int x = 0;
while (x < 11) {
  bool coin = Bernoulli(0.5);
  if(x=0)
    if (coin) x = 1 else x = 2;
  else if (x=1)
    if (coin) x = 3 else x = 4;
  else if (x=2)
    if (coin) x = 5 else x=  6;
  else if (x=3)
    if (coin) x = 1 else x = 11;
  else if (x=4)
    if (coin) x = 12 else x = 13;
  else if (x=5)
    if (coin) x = 14 else x = 15;
  else if (x=6)
    if (coin) x = 16 else x = 2;
}
return (x);
```

Figure 2.2: Translation of Discrete Time Markov Chain to a PPL [Gor14]

> "If we view the semantics of the underlying deterministic language as a map from programs to executions of the program, the semantics of a PPL built on it will be a map from programs to distributions over executions. When the program halts with probability one, this induces a proper distribution over return values. Indeed, any computable distribution can be represented as the distribution induced by a Church program in this way" [FR12]

One way to think about this notion is by considering that the program itself is the model. An example of the relation between a model (expressed in a PPL) and the implied distribution over its variables (obtained using an inference method) can be seen in Figure **??**, where a variable *flip* is set to be a Bernoulli distribution and *x* is defined in terms of *flip*. We can then see how the graphic of the inferred distributions of *flip's* and *x's* values looks like and confirm what was to be expected: for *flip's* values lower than 0.5 we see *x* follows a normal distributon, whereas for values greater than 0.5 it follows a gamma distribution instead. The goal of PP is to enable PR and ML to be accessible to most programmers and data scientists who have enough domain and programming knowledge but not enough expertise in probability theory or machine learning.

2.2.2.2 PPLs vs regular PLs

What is then, a Probabilistic Programming Language (PPL)? First of all, it can be a standalone language or an extension to a general purpose programming languag. We'll be analyzing examples of languages from either these categories in Section 2.4, but many more exist, such as as Figaro [RT15] (hosted in Scala), webppl [GS14] (embedded in Javascript) or Dimple [HBB$^+$12] (has both a Java and a MATLAB API). The key difference between these languages and a PPL is the latter has the added capability of performing conditioning and inference [ADDJ03].

```
flip = rand < 0.5
if flip
    x = randg + 2    % Random draw from Gamma(1,1)
else
    x = randn        % Random draw from standard Normal
end
```

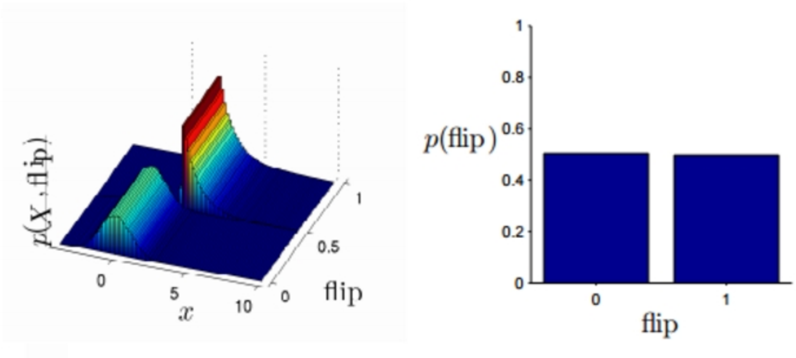


Figure 2.3: Implied distributions over variables [DL]

Conditioning is the ability to introduce observations about the real world in the program. That way, you update the prior probability based on those observations. Consider the example in Figure 2.4 (which is a simplified version of how Microsoft applies PP in its Xbox matchmaking algorithm [MWGK12]) where the prior is a normal distribution with equal parameters for all players (shown by the graphic in the top). Then, it defines how the performance of the player is based on his skill (which at the initial point in time, is equal to every one of them) and proceeds to make several observations regarding games between them. Finally, it shows the inferred probability distribution of the posterior on the bottom graphic.

2.2.2.3 Inference

We said that a PPL empowers the user to formalize a model and then query for the probability distribution of its variables, which is automatically done via inference. While general-purpose language require you to write one-time inference methods that tightly coupled to the PP you are inferring on, PPLs ship with an inference engine suited to most PP programs you can write [FMR10].

An inference engine of a PPL acts similarly to a compiler in a traditional language: rather than requiring each user to engineer its own, which requires significant expertise and is a non-trivial and error-prone endeavour, every PPL has one incorporated. Olivier Grisel called this separation of concerns between the language and its inference engine "openbox models, blackbox inference engine" [Gri13].

Having the engine work as a separate model opens up a myriad of new possibilities, mainly in the form of knowledge and tool sharing, as we have seen in the past in the compiler space. Examples of this would be new compiler compiler and interpreter techniques (such as working towards scalability or parallelization), optimizers, profilers or debuggers.

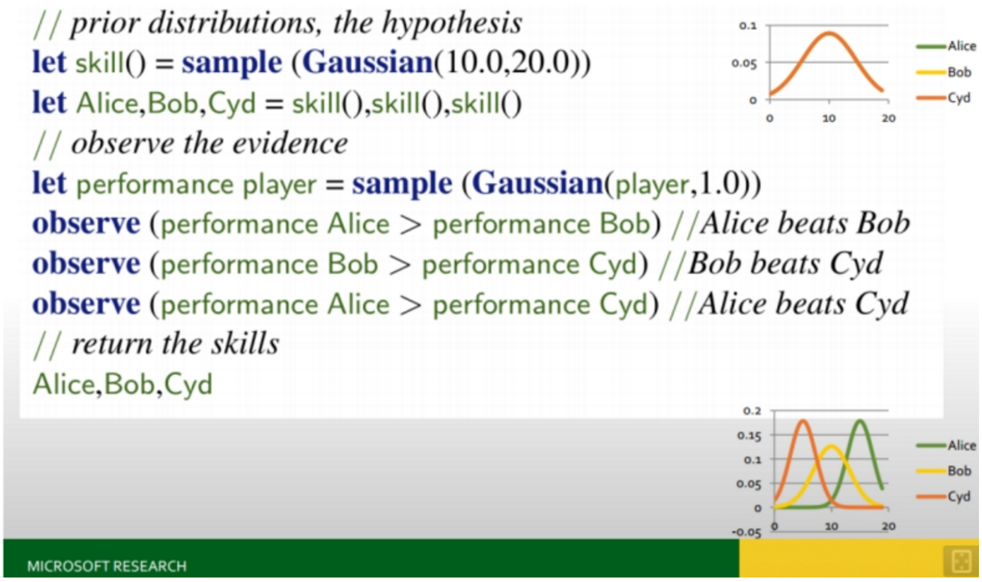


Figure 2.4: Microsoft Xbox Live True Skill [MWGK12]

Another great advantage of having a modular inference engine is that we can try different inference algorithms and pick the one that best fits the problem at hand. When analyzing if algorithm suits a certain use case, there are certain characteristics worth noting [Min99]:

- Determinism - in equal initial conditions, an algorithm always yields the same result.
- Exact result or approximation
- Guaranteed convergence - an algorithm may or not be guaranteed to reach a result at some point in time. If not, it's possible that it will run forever.
- Efficiency - related to how fast can it reach a result.

Microsoft's Infer.NET provides three inference algorithms [Res]:

- Expectation Propagation - deterministic, provides exact solutions only in some cases, is not guaranteed to converge and is labelled as "reasonably efficient".
- Variational Message Passing - also deterministic, but always gives approximates results and is guaranteed to converge. It's considered to be the most efficient of the three for most cases.
- Gibbs sampling - non-determinisc, may be able to reach exact result if given enough time to run, has guaranteed convergence and is regarded as not-so-efficient as the other two.

We can divide the three algorithms into two categories: variational bayesian methods [WBJ05][Min99] and sampling methods (in the case of Gibbs sampling, it's based on Markov chain Monte Carlo) [ADDJ03]. The main difference, as far as the end-user is concerned, is that variational methods provide faster results but are subject to bias, whereas sampling methods have the potential to produce more accurate results (the downside being it's slower and its convergence is hard to diagnose) [SAC+10].

Please notice than none of these algorithms provides the same kind of exact solution as the calculation of the joint probabilities we did in Section 2.2.1. The reason for that is that calculating an exact solution takes time exponential in the number of variables to run, even if we have smarter algorithms than the naive calculations we did [ZP94].

2.2.2.4 Openbox models

When compared to traditional machine learning methods (such as random forests, neural networks or linear regression), which take homogeneous data as input (requiring the user to separate their domain into different models), probabilistic programming is used to leverage the data's original structure. This is done by empowering the user to write his own models while taking advantage of a re-usable inference engine. Olivier Grisel called this combination "Openbox models, blackbox inference engine"[Gri13].

Rather than using most of his time performing feature engineering (that is, trying to fit the problem and the data into an existing model), the user will have the tool necessary to design the model that best fits the domain he is working on. Plus, it provides full probability distributions over both the predictions and parameters of the model, whereas ML methods can mostly only give the user a certain degree of confidence on the predictions.

2.2.3 Conclusion

Summarizing, PPLs are a step forward in using PR to solve ML problems since it helps overcome the difficulties in using PR in real world problems. This is done by adding automated general inference on top of a precise specification (the program), where in the past models were communicated using a mix of natural language, pseudo code, and mathematical formulae and solved using special purpose, one-off inference methods.

This encourages exploration, since different models require less time to setup and evaluate, and enables sharing knowledge in the form of best practices and design and development patterns.

However, using a full fleged programming language might still be an entry barrier. We want to help statisticians and data scientists alike to learn faster and be more productive using a PPL in a way similar to the tools they are accostumed to. In order to do so, we'll be combining a PPL with Visual Programming (Section 2.3).

2.3 Visual Programming

Visual Programming (VP) can be defined as "any system that allows the user to specify a program in a two-(or more)-dimensional fashion." [Mye86]. In a textual programming language, even though there are two dimensions (one being the text itself, and the other the optional line-breaking characters), only one of them has semantics, as the compiler processes text as a one-dimensional stream.

Examples of systems with aditional dimentions are ones that allow the use of multidimensional objects, the use of spatial relationships, or the use of the time dimension to specify "before-after" semantic relationships [Bur99].

Research has identified several advantages in the use of VP, such as natural expressibility, easy readability and interaction, language independence (though this is not applicable to the work of this thesis, as detailed in 2.3.1), programming at higher levels of abstraction or rapid prototyping [Jam14], which is achieved by providing immediate visual feedback [Gre95].

The advantages of programming at highers levels of abstraction are known, and one of them is it exposes users who are not used completely fluent in programming to a reduced number of concepts [Gre95], while decreasing the verbosity of programs, which can even be useful for seasoned programmers [Mye90]. It also reduces the importance of being familiar with syntax, a common cause of difficulty of adaptation among less experienced programmers when learning a new language [CTB86][CWHH05]. This difficulty of translating ideas into syntactictically correct statements can also be solved by finding alternative ways to communicate instructions to the computer [KP05].

So, the point of using a VP tool to aid in programming is to overcome the difficulties that many people have when learning a conventional language [LO87b]. It has been shown this approach can help users without prior, or little, programming experience to create fairly complex programs [Hal84]. This is specially true within certain small domains, where the language can be tailored for a subset of tasks rather than trying to be suitable for all kinds of applications [KP05]. An example of such domain would be developing ML applications resorting to probabilistic programming. Excel-like (spreadsheet) tools are a prime example of this, where the following benefits were identified [Amb87][LO87a]:

- The graphics on the screen use a familiar, concrete, and visible representation which directly maps to the user's natural model of the data
- They are non-modal and interpretive and therefore provide immediate feedback
- They supply aggregate and high-level operations
- They avoid the notion of variables (all data is visible)
- The inner world of computation is suppressed
- Each cell typically has a single value throughout the computation
- They are non-declarative and typeless
- Consistency is automatically maintained
- The order of evaluation (flow of control) is entirely derived from the declared cell dependencies

Smith and other authors claim that the human thought process is clearly optimzed for multi-dimensional data [Smi77][CC86], so all the aforementioned advantages can be explained by how graphical programming is closer to our mental representation of problems when compared to a textual interface [Car02]. As said by Fischer, Giaccardi, Sutcliffe and Mehandjiev:

> "Text-based languages tend to be more complex because the syntax and lexicon (terminology) must be learned from scratch, as with any human language. Consequently, languages designed specifically for end users represent the programmable world as graphical metaphors ... (*aim to*) reduce the cognitive burden of learning by shrinking the conceptual distance between actions in the real world and programming." [GEGN04]

This idea as been tested in an empirical study: in a algorithms course of the United States Air Force academy, students consistently show a preference for solving problems visually, while it also seems that doing so helped them achieving better scores in problem-solving exercises and overperform their colleagues who used a regular programming language [Car02]. However, shortcomes of using VP were also identified, as we will discuss in 2.3.3.

2.3.1 Visual Programming Environment

Boshernitsan proposed a classification scheme for VPLs [BD04] that divided VPLs in purely visual languages (PVLs), hybrid text and visual systems, programming-by-example systems, constraint-oriented systems and form-based systems.

In the context of this dissertation, as we want to leverage the advantages of both a VPL and a PPL while avoiding implementing a PPL, there is no other choice than using an hybrid text and visual system. We will be calling this system a visual programming environment (VPE). The difference between a VPE and a purely visual language (PVL) is that, while a PVL is a language *per se* (meaning that it there is a direct mapping between graphics and execution), VPEs offer a middle ground between regular textual languages and PVLs: they provide a graphical interface that can be used to generate code for a target language [Bur99]. An example of a PVL would be MIT's Scratch [RMMH+09] and one for a VPE is the Eclipse IDE plug-in WindowBuilder [Fou16].

If applied correctly, VPEs can help addressing some of the issues raised by critics of VP (detailed in section 2.3.3), such as VP's inhability to solve real-world large-scale problems. This is done by applying VP to only a subset of the program, making it possible to combine a general-purpose programming language with the advantages of VP [Bur99], since the code generated by a VPE can be seseamlessly integrated in any project built with its target language.

Concretely, VPEs are able to overcome the tradeoff of control for simplicity commonly made by VPLs: even if a certain idiom cannot be represented by its graphical form, the user can later edit the generated code to include it. This makes it possible to design scalable programs, both in terms of performance (since the user can still access all the target language's low-level features) and development (because all the advantages of programming visually are still present).

2.3.2 Evaluation

Even if the goal os VP is clear (to make programming more understandable, ensure correction and be faster to do) the best way to achieve it is still a matter of discussion. Like in the design of any programming language, there are some best practices to guide the design of a VPL, some of which have been identified by Burnett [Bur99] and are listed below.

- Concreteness - it's oposite of abstractness. The program express values and instances of values rather than meta-information such as types or classes.
- Directness -
- Explicitness - everything that there is to be known about the program can be easily understood by looking at the graphical representation, the user does not need to infer semantics by himself
- Immediate visual feedback - every change to the program should be immediately propagate to change in the affected output. Spreadsheets are an example of this.

However, these are just guidelines and do not guarantee the efficacy of a VPL. Whitley and Blackwell [WB97] said that, because the design decisions in a VPL lack formal basis, the only way to assess if they really contribute to facilitate the programmer's cognitive processes while programming is through empirical studies. In their studies, they have found that while subjects cited ease of learning as a benefit of VPLs, they opinions differed when asked if using a VPL had a positive impact in productivity during a project.

They also claim that there is a gap between academia and industry programmers. In contrast to the first group who tends to focus on theories of cognition to justify the use of VPL, the second is more interested in potential improvements in "potential improvements in productivity that arise from straightforward usability issues".

Some metrics that can be taken into account when assessing a VPL's efficacy are learning time, execution speed and retention [Mye90].

2.3.3 Criticism

In this section, we'll be trying to summarize some of the criticism made to VP, while proposing solutions to some of the issues mentioned and discard some of the others as non-applicable in the context of this thesis.

There are people who claim VPLs lack visual abstraction mechanisms that are as effective as those offered by text-based languages, so they are not well-suited to develop large applications [Jam14]. Some of the techniques currently used in real-world software development include iterative design and interactive prototyping, two principles that are promoted by the usage of VPLs. Also, it has been shown that the richness of the visual paradigm introduces new ways of approaching programming problems, particularly for those not trained in traditional software development methods [Jam14] (such as data scientists, which constitute the target audience of this work). Studies also shown that fairly complicated algorithms, such as garbage collection, could be described graphically [Mye90].

Green also discusses, contrary to some other evidence we discussed before [Car02][Bur99], how lab studies failed to collect evidence in favor of the productivity gain of VPLs, even though it admits user like and use them [Gre95]. He also points how that VP systems "do nothing that can't be done as well or better with straight text" and identifies the real issues as "how layout and locality can be used to convey meaning". According to our definition of VP, every system that allows the user to express himself in more than one dimension (such as using layout and locality, as proposed by Green), so it seems that the proposed alternative could be a VPL.

In his *"No silver bullet - essence and accidents of software engineering"* paper, Brooks says that *"A favorite subject for PhD dissertations in software engineering is graphical, or visual, programming—the application of computer graphics to software design.... Nothing even convincing, much less exciting, has yet emerged from such efforts. I am persuaded that nothing will. In the first place, ... the flowchart is a very poor abstraction of software structure.... It has proved to be useless as a design tool.... Second, the screens of today are too small, in pixels, to show both the scope and the resolution of any seriously detailed software diagram.... More fundamentally, ... software is very difficult to visualize."* [Bro86]. While one may be tempted to be conviced by Brooks' initial rethoric, what he wrote does not seem to apply to the work of this thesis because: a) we won't be using executable flowcharts, but rather a dataflow VPE approach, as described in **??** and b) screens are getting bigger and with higher resolutions [], a low-end screen by today's standards would be state of the art in 1986, when Brooks wrote that. The final claim that software is hard to visualize, backed by Dijkstra's letter where he states that *"I was recently exposed to ... what ... pretended to be educational software for an introductory programming course. With its "visualizations" on the screen, it was ... an obvious case of curriculum infantilization.... We must expect from that system permanent mental damage for most students exposed to it."* [D+89], is contrary to many studies done in cognitive science [LO87a][CTB86][CWHH05].

Myers admitted that the key for a successful application of VP to a real-world problem was to identify "appropriate domains and new domains to apply these technologies to" while recognizing that we have already witnessed how VP can help non-programmers work in limited domains [Mye90].

We do believe that data mining can be one of those domains (as shown by the popularity of RapidMiner) [Pia15], so it would make sense to extend the current state of the art with a tool that combines VP and PP.

solução: para ultrapassar problemas comuns de VP em sistemas reais, larga-escala, usar apenas VP em partes especificas do projeto onde VP possa ser utilizado com sucesso. usar para desenhar GUIs foi um sucesso (android, windowbuilder)

fazer programar mais facil para audiencia especifica [Bur99]

Myers also identified some of the problems that are yet to be solved regarding VP [Mye90]:

- **Difficulty with large programs or large data**. Almost all visual representations are physically larger than the text they replace, so there is often a problem that too little will fit on the screen.

  We intend to solve this issue by studying the application of some techniques that provide a greater level of abstraction in order to be able to transmit more semantics while avoiding the layout to get cluttered with details [BBB+95].

- **Poor representations**. Programs are hard to understand once created and difficult to debug and edit. The larger the size, the worse this problems becomes.

  This is related with the previous point and the proposed solution is similar.

- **Need for automatic layout**. When a program gets too large the layout becomes too hard to manage, a single addition of a piece may oblige the user to move a great number of blocks in order to avoid collisions and preserve readability. One way to deal with this would be to automatically generate an attractive layout.

  This problem is out of the scope of this thesis, although it certainly seems important for the future of VPL.

- **Lack of formal specification**. Currently, there is no formal way to describe a VPL such as the Backus-Naur Form, even if there is some work towards one was already been made [SK88].

  Again, this is out of scope, even if we will make an attempt to specify a grammar that defines the boundaries of what would be a valid graph.

- **Lack of Portability of Programs**. A program written in a textual language is as portable as a text file but VPLs require special software to view and edit.

  While the implementation of the VPE's frontend to be done in this thesis is still a matter of study and is undecided, there is the possibility of building one using the HTML/CSS/-javascript stack, making it portable across browsers for view and edition. It is also our aim to provide an intermediate representation in a data-representation format such as JSON or XML, so that a program built in a certain frontend can be processed by any other.

- **Tremendous difficulty in building editors and environments**. In 1990, each graphical language required its own editor and environment, and there were no general purpose VPL editors.

  Currently there are alternatives of re-usable frontends for VPLs, such as Blockly [fE15] or GoJS [Sof15].

- **Lack of evidence of VPLs' worth**.

  This issue was discussed in section 2.3.2, and we conclude that within certain domains (such as VP applied to PP) and target users (unexperienced programmers), there may be benifits in productivity when using a VPE.

Another question that arises is how to represent and manipulate arrays. In the empirical study made by the creators of RAPTOR, students performed statistically significantly worse on the array question when using a VPL [Car02]. This is something to consider in the future, to investigate if handling arrays functionally (by considering them as immutable values where common functions over iterable data structures could be performed, such as map, filter and reduce) could improve users' usage of the VPL.

One of the concerns of another empirical study's respondents was that high-level VPLs might deny them access to the low-level facilities of the machine that are so important in PC programming [WB97] but, as stated before, this problem is alleviated (if not completely eliminated) by using a VPE rather than a purely visual VPL, since the user can later edit the generated code, where he has access to all the language's features.

2.4 State of the Art

The purpose of this section is to try giving an overview over the existing tools currently used in either VP (purely visual VPLs or VPEs) or PPLs.

2.4.1 Stan

2.4.2 WinBUGS

2.4.3 Church

2.4.4 Infer.NET

2.4.5 PyMC

2.4.6 NoFlo

2.4.7 RapidMiner

2.4.8 Weka Knowledge FLow

2.4.9 GoJS

2.4.10 Blockly

2.4.11 Viskell

2.4.12 Eclispe Android UI Plugin

2.4.13 Eclipse Window Builder Plugin

2.4.14 VIBES

2.5 Conclusions

Chapter 3

Solution prototype

3.1 The problem it solves

As already described in Section 1.3, this dissertation aims to solve the problem of PPLs having too much of a steep learning curve for someone who is unexperienced in programming, even if that person would've enough knowledge in statistics to leverage PPLs' power in applied machine learning. We propose to do so by developing a visual programming environment for a PPL that is user-friendly and yet flexible enough to be able to program solutions for non-trivial problems.

Since the existing work joining VP with PP is still nonexistent, the notable exception being VIBES (even if it has its shortcomins, as described in 2.4.14), we have identified margin for improvement.

VPEs have been successfuly applied to other domains, and considering previous studies in VP that suggest it is well suited for both limited domains and unexperienced programmers, it is the author's belief that development in PPLs would also benefit from such a tool. Therefore, we intend to validate the following hypotehsis:

> "When a user instead of specifying a model textually, produces the model via a graphical representation that automatically translates itself into executable code, he will do so in a shorter amount of time, make fewer errors (both during development and regarding the final solution) and will reach a final representation that is more understandable and thus easier to maintain."

Because there isn't a standard method for evaluating if a language is easier to work with than another, the question arises on how to evaluate success.

3.1.1 Measuring efficiency and efficacy

The way we're planning on validating the hypothesis is through an empirical study where we compare how fast an user can define a model for a given set of problems when using a VPL in a regualr way or through our graphical interface. We'll also count the number of syntax and type erros done with each representation. By selecting users who never used the given PPL, we can not only measure execution speed but learning time.

It is valuable to assess, not only how fast can someone develop with either of the alternatives, but also the quality of the output. We plan to do so in two steps: starting by verifying if the program correctly models the problem and asking the participants in the study if they believe the model they have developed graphically is easier to understand than its textual counterpart (and vice-versa). Although subjetive, we believe getting the participants' opinion regarding the output quality could provide valuable insights in order to understand if VP can really enhance an user's experience when using a PPL. Another method we will use to help us make an assessment of the validity of the hypothesis is asking participants questions regarding usability. Even if it may seem redundant, since we would already have the time measurements, it is a way of strenghts and weaknesses.

3.1.2 Target audience

Both the study and the tool are aimed at people with knowledge in statistics who are unexperienced programmers. This may include data scientists, researchers, mathematicians or staticians. In short, anyone who would apply PP to problem solving but are not fluent in programming.

3.1.3 Expected contributions

By the end of this work, we would expect to have built a VPE for PPLs that can be extended with more PPLs, even if we are only implementing the adapter for one. By doing so we will: have a platform that enables other people to experiment and make usability research on, define a visual language that can be applied to PP in general, identifying what works and what to avoid, and ultimately assessing the viability of applying VP to PP to enhance end-user's productivity.

3.2 Outline

3.3 Architecture

3.4 Implementation

"controlled dataflow vpl"

3.4.1 Picking a front-end

3.4.1.1 Blockly

3.4.1.2 GoJS

3.4.1.3 Custom implementation

3.4.2 Picking a target PPL

3.4.2.1 WebPPL

3.4.2.2 PyMC

3.4.2.3 Infer.NET

3.4.3 Defining a Grammar

3.4.4 Handling Cycles and Conditionals

3.4.5 Handling objects and arrays

3.4.6 Inverse Compilation

3.4.7 Instant visual results

3.4.8 Opening to extension

3.5 Tutorial

3.6 Conclusions

Solution prototype

Chapter 4

Evaluation

4.1 Problems solved

4.2 Problems detected

4.3 Conclusions

Chapter 5

Conclusions

5.1 Contributions

5.2 Future Work

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