Learning Layout Design: Challenges and Opportunities

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Abstract
This position paper discusses the use of machine learning methods in layout design. Interactive layouts are pervasive and a central part of e.g. GUIs, Web interfaces, menus and forms. They have been hard to design algorithmically, because search spaces are large and multiple factors contributing to design choices. We argue that in order to touch base with real design practices, machine learning approaches should take into account the requirements posed by user-centered design. We have identified four touch points to user-centered design. For each touch point we discuss both opportunities and challenges and show results from our on-going work.

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Introduction
Interaction design is a prevalent yet challenging activity in modern software and product development. Despite its prevalence, many designers still work with paper prototypes and other analogue tools when creating and evaluating designs. Digital tools, such as Adobe Illustrator, are in use,
but generally function as sketching tools or automate very simple tasks. We argue that there is substantial untapped potential in using machine learning techniques to actively support the designer's creative work. In particular, we point out opportunities inspired by the user-centered design process: 1) automate requirement gathering, 2) offer inspirations for design, 3) automate the evaluation process, and 4) even automatically create whole layouts.

The time is ripe to discuss the potential of data-driven approaches in layout design. With the vast array of visual examples available online, and the ease of collecting large datasets on the preferences of users and their habits when interacting with software, this is an application domain ripe for the application of machine learning. In this paper we analyse a commonly used process model of user-centered design, Interaction Design Lifecycle Model [5], to identify opportunities to apply machine learning in the design process, and formulate challenges that these opportunities imply.

There is an emerging trend in this direction, both in research and industry. Recent work has studied automatic prediction of the aesthetic appeal of an interface [3]. The Webzeitgeist project [2] aims to ‘design-mine’ the web to support data-driven web design. DesignScape [4] looks at automatic generation of static graphical layouts such as fliers. However, a similar tool for interactive layouts does not yet exist. In industry, a startup named The Grid\(^1\) currently build a automated web design tool using machine learning which caught a lot of public attention. Perfectbanner\(^2\) automatically redesign web ads to increase traffic, with a machine learning algorithm that learns successful ad strategies from click data.

\(^1\)http://thegrid.io
\(^2\)http://perfectbanner.com

However, there is still substantial scope for improvement in this research area. We need better understanding of how design is created, how humans perceive layouts and interactions, and what makes a layout good. Machine learning offers tools to obtain this understanding.

**The design process and opportunities**

Taking the interaction design lifecycle model (see Figure 1), we will introduce the steps of the model, the opportunities we have identified for machine learning, and the associated challenges. Our focus is on the design of interactive layouts, whether in software or for the web.

**Establishing Requirements**

The initial step in the design process is to gather information regarding the client, the target users, and the experience and functionalities the design should support. These requirements build the fundament of the design project and all created designs have to satisfy these requirements. In the context of layout design, this involve the analysis of client side, competing products, the user group’s needs, and the functionalities the layout should provide.

Gathering information about the client and target users is currently a manual process for the designer. We see opportunities to support this process using machine
learning, especially in automatically identifying relevant online information and mentions of the client. Further machine learning could help to identify and analyse the web presence of competitors, e.g. information presented, brand colours or layout structure.

Enabling such support requires text mining of the client's current web presence (e.g. using topic modelling) and automated search to identify the sites of competing businesses. Tools to automatically classify and aggregate relevant documents about the client or their business area (such as news articles, social media, and blog posts) could also be constructed based on the results of the text mining.

The challenges here lie in automating the search process and accurately collating the relevant information. This requires the combination of techniques from information retrieval and machine learning. The models that extract the relevant information must be accurate, and robust to the diverse methods of presenting content on the web.

**Designing alternatives**

Designing alternatives is the core activity of the interaction design process. This step can be divided into two sub-activities, which are conceptual design and physical design.

The conceptual design of a layout, often referred to as wireframing, is the basic structure, which defines interactive elements, the interaction concept involved and the general structure of all elements present in the layout. The physical design refers to the more detailed specification of the design such as colour, images, menu design, and so on.

While systems which support this step exist (e.g. Adobe illustrator or Sketch), they are limited in that the designer is the only actor. Using machine learning could enable us to go beyond that by creating a second source of input — effectively allowing the system to participate in the design. Two examples would be generating ‘inspirations’ to improve an existing design or creating new layouts based on defined requirements.

This poses a number of machine learning challenges. To provide inspirations, we need to be able to classify the type of layout and the purpose of interface elements. Then this has to be matched against a database of mined designs in order to find alternative ways of presenting the information or common elements that may be missing in the current design. To generate entirely new designs, we need to mine existing layouts to create probabilities for position, size and semantic grouping of interface elements. These must be coupled with a set of design requirements to produce candidate layouts. This is an extremely complex density estimation task.

**Prototyping**

In order to test the created alternatives, the mostly static layouts have to be converted to interactive prototypes, which imitates the interaction concepts used. These prototypes do not necessarily have to be a working software.

Current prototyping tools for layout design such as InVision and Sketch have already started to support this step of the process. They offer possibilities to connect multiple layouts using simple interactions like clicks or gestures, but more complex interactions are not currently automatically integrated. This means that prototypes have to be manually programmed by the designer, e.g. with Processing, or alternative low-fidelity prototyping methods have to be considered as soon as the interaction become more complex.
Machine learning can be used to analyse flows of interaction in existing applications and automatically generate interactive prototypes based on the design alternatives produced in the previous phase of design.

Alternatively, patterns of user behaviour could be learned from software logs and used to generate probabilistic agents which can simulate interaction with the new design. This could enable early problems with a design to be identified without the significant resource cost of multiple user tests, and allow more designs to be effectively prototyped.

Creating such agents is a difficult challenge. We need a robust model of user behaviour that can classify the elements of a new interface, and generate clicks, gestures, or other inputs in a realistic fashion based on designer-specified goals. Regression models predicting how the interface will be perceived are also necessary, as well as a way of anticipating confusions between elements. Essentially, what we need is a model of failure behaviour in interaction, based on the visual layout. Clearly this a demanding task, but even a quasi-realistic agent would be very effective in improving this step of the design process.

**Evaluating**

In the evaluation step, the designer conducts tests in order to determine how usable and aesthetically pleasing a design is, and whether or not it meets the requirements. Several methods for conducting user studies to evaluate these factors are available. Depending on the result, the designer returns to an earlier stage of the process — either to rethink the requirements or create new alternatives — and iterates.

Involving the user in the design process and especially in the evaluation is a fundamental idea of user-centered design. Nevertheless, the recruiting of users, preparation and execution of studies all require significant time and resources within this iterative process. The end result is typically that only a small number of design alternatives are considered.

We see opportunities to improve the whole process of layout design by automatically testing the usability and readability of a layout, as well as an evaluation of how visual pleasing the created layout is. This will not eliminate the necessity of evaluating a layout with real users, but it will result in faster iterations and improved outcome before user evaluation. Further, it allows for checking a diverse set of designs quickly, allowing designers to explore the design space more fully.

From a machine learning standpoint, the main challenge here is automatic evaluation of readability, usability and aesthetic preference. These are all effectively complex regression problems. Given the colours, fonts, and layout of a design, we must predict how it will be perceived by users. Previous research has attempted to do this using metrics based on e.g. symmetry and grid alignment [3] or visual search models from psychology [1]. Using machine learning algorithms and crowdsourced data, there is significant potential for improvement in this area.

**Outlook**

There are many opportunities for the application of machine learning to the interaction design process. We believe that research in this area could offer significant benefits to designers, clients, and users by increasing the quality of designed layouts and producing guarantees about the quality of the results based on learned preference models.

For our own part, we see the greatest potential in the ‘designing alternatives’ and ‘evaluating’ steps of the lifecycle model. We have begun preliminary work on a number of
tools to support this activity. First, we have developed a crawler which analyses web pages and attempts to automatically group the HTML layout elements into semantically meaningful groups, using the Gestalt Laws of perceptual organization. An example output is shown in Figure 2. From this, we intend to generate probability distributions for the placement and grouping of elements, as described above, so that we can learn common patterns of web design.

These distributions will be used to improve our second tool, which is an interactive sketching application that allows designers to create wireframes for web layouts. The application suggests reorganisations and recolourings of the layout which may be more performant or aesthetically pleasing. The distributions we learn from the web crawler will be used to improve these suggestions. Currently we evaluate layouts using performance metrics like Fitts’ Law and models of visual preference from the psychology literature. In the future we hope to supplement these with machine learned models based on crowdsourced preferences for different layouts.

We hope that this paper will spur discussion on this promising research topic, and inspire new work that uses machine learning to support creativity and design.

REFERENCES