HPM: Happiness-driven Policy Making

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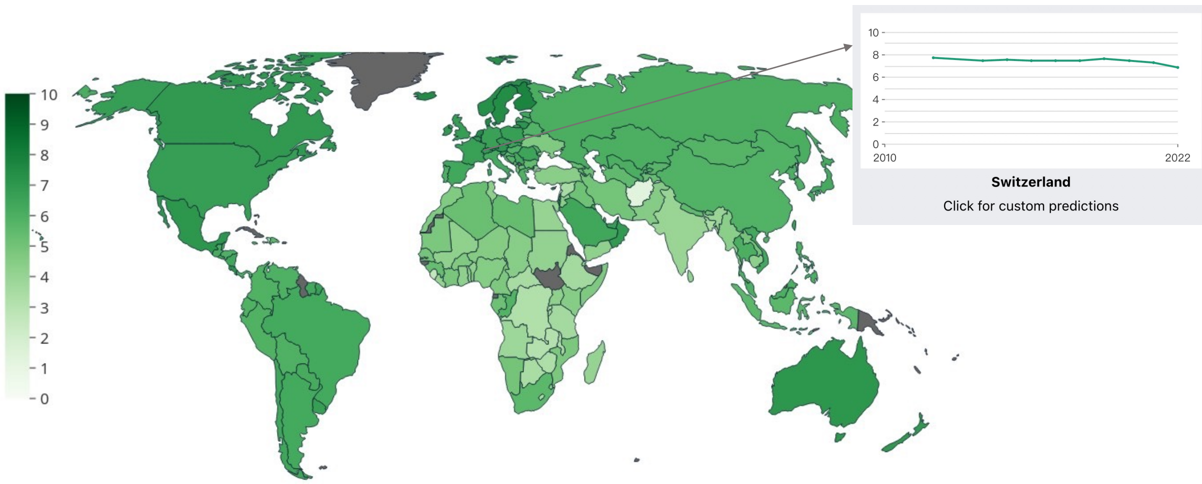

Figure 1: Choropleth map visualization of the life ladder.

Abstract

In this paper, we introduce an interactive machine-learning-based system to support policy makers in prioritizing policies to optimize the happiness level of the citizens. Our system allows the users to explore the happiness level in different countries and correlations between contributing factors. Additionally, we provide a tool that allows the policy makers to find an optimal subset of provided policies with respect to happiness level and constrained by the available budget. The suggestions are made based on the predictions of a machine learning model based on Gaussian Processes. Our system provides supportive data visualization for each of the steps.

Index Terms: Happiness level, Policy making, Explainable AI, Data Visualizations, ML Interpretability.

1 Introduction

Ensuring happiness of the citizens is a critical goal for politicians and policy makers[4]. They often need to make decisions to prioritize certain policies and projects over others to improve the well-being of the citizens and achieve certain social goals, while minimizing the implementation budget. A data-driven approach based on machine learning can provide a solid and objective basis for such decisions.

With this motivation, we introduce an interactive machine-learning-based system to support policy makers in prioritizing a subset of available policies to optimize the happiness level of the citizens. Our system allows the users to explore the happiness level in different countries as well as correlations between contributing factors. We visualize this step with a choropleth map and a parallel coordinates diagram.

The user can also use the system to input a set of policies with their expected impact on a relevant metric and get an optimal subset of policies with respect to the projected change of overall happiness level. This is done with the help of a machine learning model based on Gaussian processes. The results are presented as a donut chart and a butterfly chart.

2 Related Work

This section introduces related work from the fields of Explainable Artificial Intelligence (XAI), visual analytics, along with studies on happiness and well-being.

- **XAI and visual analytics** - As AI reaches a wider array of user groups, ranging from everyday users to model developers, the diversity in background knowledge across these groups necessitates different levels of explainability[13]. XAI can help users comprehend and verify the outcomes of machine learning models. Common XAI methods include adversarial testing[14], attribution techniques[8], and feature visualizations[9]. Visual analytics further helps bridge the knowledge gap between machine learning insights and end users. By making complex data and models more accessible and interpretable, visual analytics enhances knowledge communication and insight discovery. Key techniques in this domain include human-in-the-loop interactive machine learning[1] and predictive visual analytics[7].

- **Happiness and well-being studies** - Subjective well-being data are increasingly utilized across the social sciences to gain insights into the factors that influence individual happiness[2, 3]. The self-reported happiness level data has been analyzed using a variety of computational methods, ranging from traditional statistical approaches[11] to more advanced machine learning techniques[6, 10].

However, there is a lack of research utilizing XAI and visual analytics techniques to investigate the interplay between happiness and various socio-economic metrics. These techniques can help non-ML experts like policy-makers and end users in leveraging their domain knowledge through human-AI interactions. Our work aims to bridge this gap by providing machine learning tools to support happiness-driven policy making and effectively communicate the decision-making of the machine learning model.

3 Dataset

In this section, we introduce the datasets used in this study and describe the process of integrating them for further downstream analysis. Our study aims to build predictive models about happiness scores based on a variety of socio-economic factors. To achieve this, we curated a comprehensive dataset by aggregating two sources: the World Happiness Report[12] and Gapminder[5].

- **Happiness scores** The World Happiness Report[12] compiles cross-country data on self-reported life satisfaction, publishing "happiness scores" derived from the Gallup World Poll. This poll, conducted in over 160 countries and in 140 languages, uses the "Cantril Ladder" scale (0 to 10) to assess current life satisfaction. In this study, we sourced data from the years 2010 to 2022 inclusive. These self-reported happiness scores serve as foundational data in our study to analyze global happiness trends and predictors across various socio-economic contexts.

- **Socio-economic metrics** In addition to happiness data, our dataset includes socio-economic indicators sourced from Gapminder[5]. These indicators cover economy, education, health, environment, energy, infrastructure, work and sustainability factors that are crucial for understanding the socio-economic landscape of different countries. In this dataset, annual data for each indicator is represented by a numerical value for every country. Integrating these indicators with happiness scores enables us to explore the interplay between socio-economic conditions and subjective well-being across nations.

- **Data integration** Due to the heterogeneous nature of the datasets, we further performed a data integration process, joining datasets based on both country code and year.

4 The Visual Analytics Workspace

Our visual analytics workspace consists of two interconnected parts: the exploration page, which displays spatial and temporal distributions of happiness scores worldwide and enables users to discover common patterns among happy countries; and the predictions page, where users can interactively perform customized predictions. The two modules are linked via clicking, allowing seamless navigation between exploration and prediction functionalities.

4.1 Exploration Page

The exploration page provides open-ended data explorations and analysis interactions.

- The first subsection uses a choropleth map to visually depict the spatial distribution of happiness scores among countries, providing a straightforward and effective way to compare happiness levels across geographic regions. By hovering over a country on the map, users can instantly track the evolution of its happiness scores over time, gaining insights into temporal trends. Additionally, clicking on a country directs users to the prediction page for customized predictions for the selected country.

- In the second subsection, users can engage with an interactive parallel coordinates chart (Figure 2) where they can select specific socio-economic metrics to display. The choice of parallel coordinate charts here is driven by the high-dimensional nature of the datasets. Further, by specifying the happiness score range to highlight, users can easily discern patterns and correlations among different metrics and happiness scores. The use of query-dependent coloring and filtering makes the system more interactive and helps to mitigate over-plotting issues of parallel coordinate charts.

Figure 2: Parallel coordinate visualization of different socio-economic metrics w.r.t life ladder scores. Users can filter by years and specify the happiness score range to highlight.

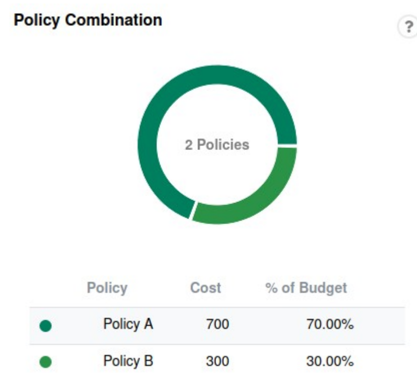

Figure 3: The model picked the combinations of policies with the largest positive impact over the life ladder, the resulting combination is shown in a donut chart.

4.2 Predictions Page

The predictions page opens when the user selects a country for further inspection. The UI presents a simple view where the user is invited to enter policies by specifying what metric the policy primarily aims to affect as well as how much it will change, how long it will take for the change to be fully effective, and how confident the user is about the accuracy of the inserted data. Since the goal is to optimize expenditures while maximizing happiness, each policy has an associated cost, and an overall budget is specified. With the click of a button the model is then tasked to pick the set of policies respecting the budget that maximize the life ladder score, it then presents multiple charts to help the user understand how the predictions are made.

- **Happiness chart**: measure of the happiness index over the next 5 years based on the new policies such as the one in Figure 3;

- **Metric changes**: predictions made by the model about how all the metrics (not just the specified ones) will change through the selected policies;

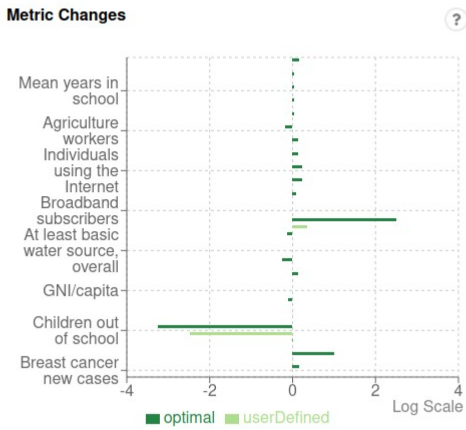

Figure 4: Comparison between optimal and user defined policy combinations, the correlation model suggests the optimal combination has a larger effect compared to the user defined one.

- **Policy Combination**: donut chart showing how much of the budget is allocated to each policy.

The user may have different expectations for what the optimal policy combination should be, to further their understanding they can pick some policies to be part of a **User Selection**, the user combination and optimal combination can then be compared using the charts outlined above. For example, seeing the difference in the affected metrics can inform the user as to why a specific policy selection was deemed sub-optimal.

5 ML Model

We use two models to predict the outcomes of the policies: a correlation model to extrapolate the effect of the policies chosen by the user to the whole set of available metrics and the second one is a Gaussian process regressor to estimate the life ladder score based on the metrics.

5.1 Correlation Model

The user only changes one metric per policy but this single change should be reflected in all the related metrics. This simple model aims to achieve this goal by correlating the changed metric with all the others, and updating them as necessary. The metric changes are then spread over the period specified by the user and bounded to remain within the domain of each metric. This results in an input such as the one in Figure 4, taking all metrics into consideration and ready to be fed into the next model.

5.2 Gaussian Process Regression

The second model is a Gaussian process regressor with a dot-product kernel, it is used to be able to estimate uncertainty on the life ladder score. The data first passes through a few steps of data-cleaning:

- scaling using a standard scaler;
- imputation using KNN to take advantage of the similarity between close points;
- removal of columns which are very highly correlated, since they don't add a lot of information;
- feature selection, the best columns are picked based on the regression score, using *f_regression* as metric.

The model is then trained on a subset of the data, with the remaining portion of the set dedicated to validation. The elements composing the data pipeline, as well as the model, are then stored in a python 'pickle' file so they can be easily reused without needing to re-train the model whenever predictions are necessary.

6 Use Case

The main use case of our system is supporting policy makers who have a large number of policies for choice and desire a data driven recommendation on which policies to prioritize. The exploration page allows policy makers to understand the global context of the happiness metric by comparing the historic data for different counties on a map. Additionally, the parallel coordinates diagram provides the user with a possibility to analyze how the contribution of various factors to the happiness score are correlated and what patterns can be detected.

The prediction page is mostly useful for policy makers who need to select a subset of available policies, being constrained by the budget. By entering the expected impacts of the policies into our tool, they can get an output of a set of policies that in total does not exceed the budget and achieves the largest happiness improvement of all available combinations. Thanks to the visualization of the output, users can compare and analyze the suggestion independently and take it into consideration as one of the factors when making decisions.

7 Discussion

Overall, our system provides an interactive way for policy makers to integrate machine learning technologies into their decision making process. This tool is simple to use, allows the users to explore the worldwide context of happiness scores, and makes visualized suggestions for policy choices with explanation of contributing factors and correlations.

The main limitation of our system is that its design is based on our estimation of the needs of policy makers and assumptions we made about their decision making process. We did not have the resources to conduct a targeted user study to get feedback and iterate over the design. Such a user study is a crucial part of ensuring the usability of the system, therefore it remains as the main goal for the future work.

Another potential improvement targets the model we used in the backend of our system. Currently, the model only considers correlation but not causation. As one of the main next steps, we could build out our model and make its architecture more sophisticated.

8 Conclusion

We presented an interactive machine-learning-based system designed to assist policymakers in prioritizing a subset of available policies to enhance citizens' happiness. The system enables users to explore happiness levels across various countries and analyze correlations between contributing factors as well as prioritize available policies with respect to predicted change in happiness levels. It has high potential in making the decision process of policy makers more data driven but it still needs to be validated and adjusted.

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