ICE: An Interactive Configuration Explorer for High Dimensional Categorical Parameter Spaces.

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Abstract—There are many applications where users seek to explore the impact of the settings of several categorical variables with respect to one dependent numerical variable. For example, a computer systems analyst might want to study how the type of file system or storage device affects system performance. A usual choice is the method of Parallel Sets designed to visualize multivariate categorical variables. However, we found that the magnitude of the parameter impacts on the numerical variable cannot be easily observed here. We also attempted a dimension reduction approach based on Multiple Correspondence Analysis but found that the SVD-generated 2D layout resulted in a loss of information. We hence propose a novel approach, the Interactive Configuration Explorer (ICE), which directly addresses the need of analysts to learn how the dependent numerical variable is affected by the parameter settings given multiple optimization objectives. No information is lost as ICE shows the complete distribution and statistics of the dependent variable in context with each categorical variable. Analysts can interactively filter the variables to optimize for certain goals such as achieving a system with maximum performance, low variance, etc. Our system was developed in tight collaboration with a group of systems performance researchers and its final effectiveness was evaluated with expert interviews, a comparative user study, and two case studies.

1 INTRODUCTION

Visual analytics of multivariate categorical data with numerical dependent variables is crucial in many different applications, including

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tasks that often recur in similar parameter spaces: optimization, partitioning, outliers, fitting, sensitivity and uncertainty. Our objective is to support optimization, partitioning and sensitivity analysis of the parameter space with an expressive visual interface. ICE can be used to analyze the spread of the dependent numerical variable with respect to every parameter. Also, the parameter space can be partitioned with interactive filtering based on user goals.

Most existing parameter-visualization methods decompose a high-dimensional space into a matrix of small multiples, each showing the relation among two parameters. Some researchers use bivariate scatter-plot projections of the full space while others use HyperSlices, a set of orthogonal 2D slices, each holding the target configuration as a center focal point [5,52]. The shortcoming of such methods is that they only show two parameters per plot, turning the quest for insight about multivariate relationships into a visual search across the plots, requiring mental fusion of disjoint relationships. Also, only a few techniques exist for analyzing the parameter spaces of categorical variables, such as Parallel Sets [37] and SVD-based displays generated by Multiple Correspondence Analysis [20]. These visualization techniques can be classified mainly into two types: (1) dimension-reduction techniques for categorical data and (2) data splitting based on categorical features. Both techniques suffer from certain shortcomings.

One of these shortcomings is information loss. For techniques based on MCA and similar dimension reduction procedures, the generated layout suffers from information loss. For complex datasets, parameter relationships might not be preserved in lower dimensions, which can result in a misinterpretation of the parameter space.

Another shortcoming is that the existing techniques are not overly well suited for visually optimizing multiple objectives at the same time. Consider a systems engineer who wants to filter configurations based on high throughput and small throughput variance simultaneously. These two user goals in this case are the objectives for searching through the parameter space which have to be optimized simultaneously. Visualizing the parameter space in context of the dependent numerical variable for multiple objectives is not possible with dimension-reduction techniques. Parallel Sets, on the other hand, allow for multi-objective filtering but the polylines or sectors can become too cluttered as the number of variables and levels in the dataset increases.

We collaborated with a group of computer systems researchers who faced exactly these challenges. We began with assessing the requirements of an effective visualization tool that would effectively enable them to study a set of categorical variables in context of a numerical dependent variable in light of multiple optimization objectives. Based on an analysis of these requirements we then iteratively derived a novel approach for this purpose, called the Interactive Configuration Explorer (ICE) that is subject of this paper.

ICE is a tool especially designed for tuning a large number of categorical parameters, for objectives based on a dependent numerical variable, like in computer system performance optimization [9] where the objective is based on the throughput behavior of the system. One of the important reasons for developing ICE is to assist the analyst in visualizing the search space at every stage in the optimization process. Hence, the parameters are visualized based on the range and distribution of the dependent numerical variable they span. This representation is free of any information loss because the categorical variables are not transformed into numerical variables but are studied as individual identities, hence preserving the properties for both ordered and unordered categorical variables. We evaluate ICE for performance, effectiveness and generality with the help of two case and two user studies. The main contributions of our work are:

- Visualize a greater number of categorical variables with a view facilitating comparison between all parameter levels.
- Assist in multi-objective optimization based filtering on large parameter spaces.
- Compare multiple configurations (set of parameters) based on their impact on the dependent numerical variable.

Our paper is organized as follows. Section 2 presents related work. Section 3 presents the dataset and domain setting we used to gain a practical backdrop for this otherwise rather general design. Section 4 presents a requirement analysis characterizing these types of applications. Section 5 describes our methodology, the ICE, along with two case studies rooted within the systems domain. Section 6 presents some helpful implementation hints. Section 7 outlines a thorough evaluation we performed with a set of more general case studies to show the generality of our tool. Section 8 concludes.

2 RELATED WORK

In this section, we will discuss the existing techniques available for studying mixed multivariate datasets including both categorical and numerical attributes applied in related domains [25, 65]. The main objectives of visual analytics in these domains includes the study of correlations between categorical variables and clustering in the parameter space with projection methods (fused displays and dimension reduction techniques) or parallel sets.

2.1 Techniques to study correlation

There are multiple specialized techniques available to study correlation between features in high-dimensional data. Since the data in consideration is categorical with one dependent numerical variable, most techniques like Pearson correlation will give ambiguous results. Hence, specialized correlation methods like Cramer’s V (based on Chi-squared statistic) are used [4, 17]. There also exist statistical tests for correlating categorical variables by comparing their behavior on numerical variables, like T-test, chi-square test, One-Way ANOVA and the Kruskal Wallis test. Techniques also exist to study correlation of multivariate temporal data [10, 62]. However, for datasets with very high dimensionality, it can be hard to study correlations in the overall distribution of the dataset. Hence, methods to study correlation on large datasets over parts of the distribution have been devised [58]. The results from these techniques can then be used as input to fused displays where these correlations are visualized in the form of scatter-plots and networks [69].

2.2 Clustering techniques

Since most categorical data consist of unordered nominal values [71], most clustering algorithms are not directly applicable to study categorical parameter spaces. Advanced techniques like k-mode [30], SQUEEZER [24] and COOLCAT [3] have been developed to work especially on categorical data. Some of the latest research has focused more on advanced clustering techniques in a supervised learning environment [64] based on human perception. All of these techniques differ based on the similarity criterion used for clustering as different similarity criterion are designed to capture specific relationships in the data. However, in multi-objective filtering scenarios, clustering as a concept is limited in its scope as each algorithm captures only a particular relationship in the dataset based on the similarity criterion.
2.3 High dimensional Data Visualization techniques

Projecting high dimensional data into lower dimensions is another technique to visualize relationships between attributes and the data points. Scatter-plot matrices [23] is a way to visualize pairwise relationships between the variables in which multiple plots are generated where each plot compares two attributes from the dataset. Different variations of this technique include bivariate scatter-plot projections of the full space and HyperSlices based approach [5, 52]. However, all of these techniques do not scale with the number of attributes as the number of plots increases exponentially. This makes it difficult to mentally fuse the disjoint relationships obtained from individual plots. Similarly, 3D volume datasets can be represented with Multicharts [15] and dynamic volume lines [66] but these techniques are also limited in their application domain.

Parallel Sets [37] is another popular method for visual analytics of multidimensional categorical data. It maps data into ribbons which subdivide according to the percentage of the population they represent. Each categorical variable is mapped to an axis which is divided into sections according to the percentage of data contained in each category (see Figure 3 (right)). However, as the number of parameters in the dataset increases, the plot can become too cluttered to project any useful information. An example parallel sets plot of our system performance data is shown in Figure 3 (right), showing the excessive overlap of ribbons with only five variables. The complete parallel sets plot is given in the supplementary material.

Another class of dimension reduction techniques include MDS [38, 39], PCA, Kernel PCA, locally linear embedding (LLE) [54], Fisher’s discriminant analysis [47], spectral clustering [49] and t-distributed stochastic neighbor embedding (t-SNE) [45]. Although these techniques have been designed to work with numerical data, categorical data can be converted to numeric form and can be visualized using these techniques. To convert categorical data into numerical format, we can use one-hot encoding or the re-mapping technique described by Zhang et al. [70]. These methods are good for visualizing relationships between the datapoints but their effectiveness decrease as the dimensionality of the dataset increase. An example case is shown in Figure 2 where no clear clusters based on the dependent numerical variable (throughput) could be seen with spectral clustering and t-SNE on the systems performance dataset.

To better cater the need of projecting a larger number of dimensions to lower dimensions, another class of multi-variate projection techniques exist which arranges variables in a radial layout e.g. Star Coordinates [33, 34, 40] or RadViz [14, 21, 28]. Both of these techniques are similar as they generate a radial layout with variables as anchor points on the circumference of a circle and the data points are systematically placed inside the circle based on their value for each variable. Star coordinates project a linear transformation of data while RadViz projects a non-linear transformation [55]. These projection techniques work well to project and visualize clusters in high dimensional numerical data [50]. Also, Star coordinates and RadViz can be combined to create a smooth visual transition over multiple dimensions of the data to visualize multiple dimensions of the dataset interactively [41, 42]. While these techniques work well for numerical data, they cannot be applied directly to categorical parameter spaces. A variation, concentric RadViz [51] can be used to study different categorical variables as concentric RadViz circles but the main objective is to study data distribution for given parameter combinations. However, the correlation between different categories cannot be visualized with this technique.

Another technique, Multiple Correspondence Analysis (MCA) [20] is specifically designed for projecting categorical data. Numerical data can also be visualized with MCA by discretizing it into categories. It can be used to generate fused displays in which the levels of categorical variables are plotted within the same space than the data points. Similar to PCA, one can select a bivariate basis which maximizes the spatial expanse of the plot. In these displays the distance between two points represents a notion of association. As shown in Figure 3 (left), MCA is effective in visualizing associations among the levels of the categories. However, there is a certain loss of information due to the omission of the higher order basis vectors. It also tends to get cluttered when the number of data points (the parameterized configurations) or even the number of categories and levels grow large.

3 DATASET

While our method readily applies to any categorical dataset with a numerical (or categorical) target variable, our specific use case was to support a team of systems researchers in their aim to learn about the impact of configuration choices on throughput and its variability in a benchmark computer system. The dataset we used had been collected over a period of three years in the research team’s lab at our university.

A set of several experiments were run to measure the system performance for a large number of configurations. Currently, the dataset consists of 10 dimensions with 100k configurations and about 500k data points.
points (i.e., system configurations that were each executed on average five times to ensure stable results). The attributes in the dataset include Workload Type, File System, Block Size, Inode Size, Block Group, Atime Option, Journal Option, Special Option, I/O Scheduler, and Device type. All of these variables are categorical where a configuration is a set of categories from at least one of these variables. Some of these variables are ordinal (e.g., Block Size can be 1KB, 2KB, or 4KB only) while others are nominal (e.g., JournalOp can be writeback, ordered, journal, or none). The dependent numerical variable is the Throughput of each parameter configuration.

Direct optimization techniques have been applied to search for optimal configuration in such large parameter spaces. Some of the applied techniques include Control Theory [43, 44, 72], Genetic Algorithms [18, 29], Simulated Annealing [13, 36] and Bayesian Optimization [57]. However these techniques prove to be too slow and sometimes result in sub-optimal solutions as our experiments confirm [9, 68]. Hence, there is a need to visualize the search space and the efficacy of the search techniques. Our ICE tool helps in visualizing and filtering these large parameter spaces to learn about optimal settings and trade-offs for the underlying system's performance.

4 REQUIREMENT ANALYSIS

To systematically evolve our ICE tool with the needs of the systems researchers in mind, we applied Munzner’s nested model for visualization design [46, 48]. Building the ICE tool following the nested model greatly helped in the step-by-step development with proper evaluation at each stage of the implementation. The first of the four stages of developing the eventual visual tool was to gather, from the domain experts, a list of requirements expected to be met by our tool. Our many discussions culminated in the following list of seven requirements:

R1: Statistics visualization. System researchers are typically interested in assessing the impact of a parameter on throughput via statistical measures. Hence, the framework should display the Mean, Median, some Percentiles, Min, Max, Range and Distribution of the resulting throughput for each variable independently. Visualizing a complete distribution curve is important to prevent any incorrect statistical information. For example, the mean of a bimodal distribution and a normal distribution might be the same, but they are different distributions requiring different systems approaches to optimize. A full distribution curve of the data can complement the statistical information, thus preventing any wrong conclusions about a parameter.

R2: Comparative visualization. Comparing the impact and trade-offs of different parameters on system throughput is crucial for choosing the best configuration in such a large parameter space. The ability to compare different parameter settings helps analysts to determine the right set of parameters by repeated selection and filtering to arrive at the desired system performance.

R3: Filtering. When dealing with large parameter spaces, choosing a system configuration with the best performance is non-trivial. Filtering by choosing the best parameters iteratively can reveal complex hierarchical dependencies between the parameters and system throughput. For example, assume analyst Mike seeking to optimize a system running a database server workload. He can first choose the best File System type, followed by the best Block Size and so on until there is no more improvement in the system performance.

R4: Support informed predictions. As discussed in R4, filtering is important for reducing the large parameter space to a smaller space of interest. Yet, guidelines are needed that can help an analyst choose the right parameters to reach a desired goal. Assume analyst Jane who has a system running a Database server workload and a File System of type ext2. Now she wishes to choose the system configuration which gives a minimum variation in the performance: i.e., the narrowest range of throughput thus yielding a “stable” throughput behavior. To achieve these goals, the visualization scheme should provide the necessary cues.

R5: Provenance visualization. Iterative filtering is useful but it needs to be attached to a visual provenance scheme where the analyst can keep track of the progress at each stage in the filtering progress. Likewise, the analyst should be able to move back to any past state in the pipeline to undo any actions if required.

R6: Aggregate view. Requirements R1-R4 focus on analyzing the impact of throughput with each parameter in the dataset where the goal is to assist in informed predictions. At the same time, the interface should also give a summarizing view of the span of throughput performance that is reachable with the evolving system configuration. During our meetings with the systems research team, we soon realized that they currently had very few visual tools at hand to analyze their large parameter spaces with these seven requirements in mind. They were open to the use of visual tools, but they strived for easy-to-understand traditional visualization tools, as opposed to highly specialized designs with a possibly steep learning curve. Their motivation was to develop a tool that would gain wide acceptance within the systems-research community and use well recognized standards and metrics, made visual and interactive via our tool.

We also concluded that dashboards with standard visualizations, such as bar, line, and pie charts were insufficient to fully capture the requirements we collected, at least not in an easy and straightforward manner. Other visualization paradigms such as parallel sets and MCA plots were similarly ruled out (see our study in Section 2.3 above).

We thus needed to find a balance between an advanced visualization design and one that would convey the established performance metrics in an intuitive way. We believe that the emerged design and the lessons learned throughout the process are sufficiently general and apply to domains much wider than computer systems analysis.

5 INTERACTIVE CONFIGURATION EXPLORER (ICE)

The ICE interface is divided into three components (see Figure 1). The first section is the Parameter Explorer (A). Its design satisfies majority of the requirements (R1 to R4) as it visualizes and allows users to tune the target variable’s distribution for each parameter in the dataset. It allows the analyst to turn off parameters that are deemed irrelevant as well as filter out configurations with unwanted or non-competitive parameter level settings, both by toggling on/off the parameter and parameter level (category) bars, respectively, enabling the user to conduct the iterative optimization of the target parameter, system throughput in this case. It also supports zooming and panning for better comparison of the bars. To the right of the Parameter Explorer is the Aggregate View (B). The Aggregate View displays the throughput distribution for the configurations selected in the Parameter Explorer, thus satisfying requirement R6. The third component of the ICE is the Provenance Terminal (C). It satisfies requirement R5 and allows the user to easily track, roll back, and edit the parameter filtering progress.

5.1 The Range-Distribution (R-D) Bars

Sections A, B of the ICE interface consist of a set of Range-Distribution (R-D) bars. Each bar contains the probability distribution function with additional statistical information about the dependent numerical variable. The R-D bars are arranged and delimited similarly to a vertical Gantt or timeline chart, with one bar dedicated to one parameter level, and are grouped by the variables. The lower/upper limit of each bar is determined by the lowest/highest value of the dependent numerical variable that can be achieved for all configurations with the parameter level the bar represents.

A completely annotated bar displaying the information that each part of the bar contains is shown in Figure 4. Each bar is a sequence of combinations of grays which represent the range of percentiles. The color codes are chosen with the help of ColorBrewer [22] to show a continuous diverging effect of percentiles on the bar. The magenta region shows the distribution of the target variable over the range. Statistical information is shown with lines separating the percentile ranges and a black dot displaying the mean value. See Section 5.6 for more detail on how we arrived at these specific design choices.

5.2 Parameter Explorer

The Parameter Explorer is designed for the goal of visualizing a numerical variable with respect to individual parameters in the dataset: i.e., the requirements R1 to R4. As mentioned, multiple bars are stacked, grouped by parameters and their levels. This grouping allows for easy comparison of the impact of numerical variable on the parameters. As
where at the finest level one line is drawn for each data point, or groups
workload. Similarly, all parameters can be correlated based on user
with each bar containing the information about the impact on the de-
variation in the throughput as compared to the system running a
variable is shown as a magenta distribution curve. The grouping of bars
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several parameters in a single screen for quick comparison and filtering
levels in
level
is selected (level name shown in black) and the remaining
is toggled off by the analyst, so it is not considered in generating the aggregate view. This satisfies
filtering requirement R3.
We specifically designed the Parameter Explorer to accommodate
many parameters in a small space. One bar is generated for one param-
eter, and depending on the screen size, analysts can accommodate
parameters in a single screen for quick comparison and filtering
of the parameter space. Compared to parallel sets (Figure 3, right),
where at the finest level one line is drawn for each data point, or groups
of identical data points (see bottom portion of the plot), the space effi-
ciency of ICE in displaying parameter levels is highly optimized. The
simple stacked bars concept of ICE prevents the data cluttering that
plagues the parallel sets since it captures the configuration statistics
succinctly in each bar. Figure 5 shows a portion of the Parameter Ex-
plorer for the system performance dataset. The complete view of
the Parameter Explorer is available in the supplement material.

The analyst can click on the level label to toggle it. Parameter Ex-
plorer and the Aggregate View are updated based on the filtered param-
eter space data. In this way, analysts can iteratively move closer to the
configurations with the desired value of the target variable, throughput.

shown in Figure 5, the level names are listed underneath each bar and
the parameters are shown as buttons below the group of levels. The bars
for each variable are grouped within a blue box. The statistics (mean and percentiles) are shown as alternating shades of gray for each param-
ter level, hence partially satisfying R1. The distribution of dependent variable is shown as a magenta distribution curve. The grouping of bars
with each bar containing the information about the impact on the de-
pendent variable clearly reveals the correlation between the parameters
levels, if there is any. For example, in Figure 1, the Workload:Dbsrvr
and wbsrvr can easily be compared based on the throughput
values they span. A system running a wbsrvr workload has much less
variation in the throughput as compared to the system running a dbsrvr
workload. Similarly, all parameters can be correlated based on user
objectives for a system optimization. This satisfies requirements R2
and R1.

Analysts can use the Parameter Explorer to filter within a large set
of possible configuration spaces. As shown in Figure 5, the user has the
ability to select one or more levels for each parameter; for example, the
level dbsrvr is selected (level name shown in black) and the remaining
levels in Workload are not (level names shown in red). Also, the user
can completely select or remove a parameter from the dataset; for example, Block Size (button shown in red) is toggled off by the analyst,
so it is not considered in generating the aggregate view. This satisfies
the filtering requirement R3.

The Provenance Terminal (see Figure 6) is used to keep track of the
progress of the iterative filtering activities. In this process, the analyst
might want to toggle between multiple parameter configurations to
compare the resulting dependent variable distributions. The Prove-
nance Terminal can be used to see and compare the dependent variable
ranges for the various iterated parameter configuration. It also allows the analyst to roll back to a previous parameter configuration if the
evolution gets stuck without hope to further improve it. This satisfies
requirement R6. The maximum value of the dependent variable at each
stage of the selection is shown with a red circular pointer on a red line,
while the minimum value is shown with a blue circular pointer on a blue line. This view is updated with each user interaction.

An example use case of the Provenance Terminal can be that of a
system administrator searching for the best configuration but with a
minimum variation of the throughput. The latter will reduce the uncer-
tainty in the predicted performance when the found parameter settings
are applied in practice. The analyst would start off by selecting (Work-
load:Dbsrvr → FileSystem:Xfs) as shown in stages 1–5 in Figure 7.
We see that the minimum and the maximum throughput values almost
converge to a very small range, but the maximum throughput value is
compromised. To correct this, the analyst can go back to stage 4 by
clicking on the red or blue pointer. This leads to a replication of this
stage at the end of the chain as stage 6. Now the analyst can take a
different path to get a better overall throughput while simultaneously
optimizing for minimum throughput range: i.e., stages 7–8 in Figure 7
(Workload:Dbsrvr → FileSystem:Ext2 → InodeSize:128). In this way,
the Provenance Terminal helps in comparing multiple configurations:
i.e., comparing steps 1–5 (configuration 1) and steps 6–9 (configuration 2).

Aggregate View

The Aggregate View, located to the right of the Parameter Explorer
in Figure 1 displays a single R-D bar. While the main purpose of
each Parameter Explorer R-D bar is to convey the dependent numerical
variable distributions possible if the respective parameter level is chosen,
the Aggregate View communicates the distribution possible with all
currently selected parameter levels. As such it can be used to quickly
visualize the impact of a transition from one parameter configuration
to another. Whereas the Provenance Terminal summarizes the top
and bottom end of the achievable dependent variable’s value only, the
Aggregate View offers detailed distribution information for the current
parameter configuration.

Interaction with ICE: Two Case Studies
To get a sense for how analysts would interact with ICE we present
two use cases involving the systems performance dataset. One practical
application is to analyze a system’s performance stability. Systems
vary greatly in their performance for different workloads which can be
quantified by the aforementioned range, i.e., the difference between the maximum and the minimum throughput for a particular configuration [8]. A large range means less stability and less predictability. The first use case shows how one would optimize a system running a mail server workload. Figure 8 shows the steps involved in the filtering process. First, the analyst selects the workload type as Mail Server by clicking the respective label. The File System throughput values change as shown in the first step in Figure 8. The primary concern here is to minimize the variation in the throughput for a more stable and predictable mail service. The analyst can clearly see that choosing the btrfs File System gives the minimum throughput range and thus is more stable and predictable for the user of the service. While its overall throughput is lower than for ext2 and ext4, these File Systems are less reliable and would leave users of the mail service often frustrated.

However, sometimes there is a situation when the user cannot change the File System (i.e., because it requires a costly disk reformat and restore), and thus it has to be set to ext4 regardless of the application. Such cases are quite common in practice, when it is not possible to change some parameters of the system. In such a case, the analyst can return to the previous state of filtering by ways of the provenance terminal. After selecting the ext4 File System, the next parameter to tune is the block size which has throughput values as shown in Stage 2 of Figure 8. Comparing the throughput distributions for each level in block size, the user selects block size of 1024 since it results in the highest throughput value with minimum variation. After choosing Block Size = 1024, the parameter explorer view is updated with new throughput distributions for each parameter level. The next parameter the user can filter is the device type, shown as Stage 3 in Figure 8. For the given configuration, the device type sas cannot be chosen since there is no sample with such configuration in the dataset. The label is henceforth colored red. Now the analyst can select either a sas or sata device. This presents a trade-off where sas has a lower range while sata gives a higher throughput.

5.6 Design Alternatives

There were four design alternatives which we had to choose from. In this section we discuss why we chose the current design of the ICE tool given the alternatives.

- R-D bars instead of box plot: Box plots are great for representing the distribution of data with the help of percentiles, but they show only fifty percent of the data (i.e., from 25th to 75th percentile). They also assume that the data points are normally distributed which can be restrictive: it certainly is a restriction in our application as is apparent in the distributions shown in any of the R-D bars.

- R-D bars instead of parallel sets: Bars make it possible to represent the parameters and their levels in a smaller space as compared to parallel sets. The R-D bars also prevent data cluttering because they capture the configuration statistics succinctly without the need to draw individual lines (see also Section 5.2).

- Displaying the distribution: Violin plots [27] and bean plots [32] are better in displaying distributions, as opposed to
Where regular searching for a categorical parameter level has To filter and display large amount of data in real time is challenging. Terminal. values with each user request. With every interaction, the Filtering en-

specialized data structures [16, 19, 53, 60].

time complexity ($O(NM)$) complexity, one-hot encoding has $O(N)$ time complexity ($N$ is the number of datapoints and $M$ is the number of parameter levels). Another benefit of using one-hot encoding is that it generates a sparse version of the dataset which is easier for the modern systems to process with specialized data structures [16, 19, 53, 60].

For the requirement to display distribution curves for each parameter level, the time to display the filtered data also needs to be optimized. If we try to use every datapoint in the calculation of the distribution, the time to display the visualization would not scale well with the size of the dataset. The time to display full data on our dataset with around 100k configurations is around 1,400 milliseconds, which is too slow. Hence, sampling of the data is required to estimate distributions. We evaluated the trade-off between information loss with random sampling and the time to display the data. Figure 10 shows that as the distribution similarity ($p$-value) of the complete and sampled dataset increase, the time to generate the visualization also increase. To measure information loss with sampling, we used the Kolmogorov-Smirnov test by comparing data distribution from the sampled dataset with the complete dataset.

After evaluating the loss of information with sampling and the time to display the visualizations, a sample size of 20% proved to be an appropriate option. This is because the display time curve has a steep increase as we go to higher sample sizes but the the $p$-value does not increase much after 20%—hence a good trade-off. ICE on the systems performance dataset uses 20% of the full dataset (20k data points) which takes around 800 milliseconds of display and filtering time. These results also give a good threshold for dataset size which can be fully displayed with ICE without sampling. In the current implementation of ICE, the datasets with less than 20k data points are processed without sampling. For larger datasets, the sample size is determined when the $p$-value crosses a .5 threshold.

To filter and display large amount of data in real time is challenging. ICE is optimized for filtering speed using one-hot encoding filtering and random sampling. One-hot encoding is used to convert categorical data to binary variables for faster processing with no loss of information. An example of converting the categorical data to numerical with one-hot encoding is provided in the supplementary material. This technique greatly reduces the time complexity of searching for a parameter level. Where regular searching for a categorical parameter level has $O(NM)$ complexity, one-hot encoding has $O(N)$ time complexity ($N$ is the number of datapoints and $M$ is the number of parameter levels). Another benefit of using one-hot encoding is that it generates a sparse version of the dataset which is easier for the modern systems to process with specialized data structures [16, 19, 53, 60].

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<table>
<thead>
<tr>
<th>Dataset</th>
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<tbody>
<tr>
<td>100k configurations</td>
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<td>20k data points</td>
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### 6 IMPLEMENTATION

Figure 9 shows the block diagram of different components of our ICE tool. There is a backend server consisting of a Database, Filtering Engine, and a Provenance Stack. The frontend consists of a Visualization Engine which runs in a browser. The backend is a python flask server and the frontend is created with D3 [6]. A database stores the original dataset which can be uploaded from the ICE interface.

The Filtering engine updates the existing data based on a user request from the Visualization engine. The data is then grouped separately for the Parameter Explorer and the Aggregate View and sent to the Visualization engine for display. Another component to the backend is the Provenance Stack, which keeps track of the dependent variable values with each user request. With every interaction, the Filtering engine updates the Provenance Stack which then updates the Provenance Terminal.

#### 6.1 Data filtering

To filter and display large amount of data in real time is challenging. ICE is optimized for filtering speed using one-hot encoding filtering and random sampling. One-hot encoding is used to convert categorical data to binary variables for faster processing with no loss of information. An example of converting the categorical data to numerical with one-hot encoding is provided in the supplementary material. This technique greatly reduces the time complexity of searching for a parameter level. Where regular searching for a categorical parameter level has $O(NM)$ complexity, one-hot encoding has $O(N)$ time complexity ($N$ is the number of datapoints and $M$ is the number of parameter levels). Another benefit of using one-hot encoding is that it generates a sparse version of the dataset which is easier for the modern systems to process with specialized data structures [16, 19, 53, 60].

For the requirement to display distribution curves for each parameter level, the time to display the filtered data also needs to be optimized. If we try to use every datapoint in the calculation of the distribution, the time to display the visualization would not scale well with the size of the dataset. The time to display full data on our dataset with around 100k configurations is around 1,400 milliseconds, which is too slow. Hence, sampling of the data is required to estimate distributions. We evaluated the trade-off between information loss with random sampling and the time to display the data. Figure 10 shows that as the distribution similarity ($p$-value) of the complete and sampled dataset increase, the time to generate the visualization also increase. To measure information loss with sampling, we used the Kolmogorov-Smirnov test by comparing data distribution from the sampled dataset with the complete dataset.

After evaluating the loss of information with sampling and the time to display the visualizations, a sample size of 20% proved to be an appropriate option. This is because the display time curve has a steep increase as we go to higher sample sizes but the the $p$-value does not increase much after 20%—hence a good trade-off. ICE on the systems performance dataset uses 20% of the full dataset (20k data points) which takes around 800 milliseconds of display and filtering time. These results also give a good threshold for dataset size which can be fully displayed with ICE without sampling. In the current implementation of ICE, the datasets with less than 20k data points are processed without sampling. For larger datasets, the sample size is determined when the $p$-value crosses a .5 threshold.

#### 7 Evaluation

In this section, we evaluate our ICE using the techniques suggested in the nested model-based visualization design literature [46, 48]. We first used the Analysis of Competing Hypotheses (ACH) [26] method as a mechanism to efficiently identify which of the existing techniques (see Section 2) would need to be formally compared with ours via a user study. The ACH is a methodology for an unbiased comparison of a set of competing hypotheses, in our case the various visualization techniques in terms of the requirements put forward in Section 4.

The ACH showed that only ICE and Parallel Sets could satisfy all formulated hypotheses. We did not consider hypotheses comparing the goodness of a visualization or the effectiveness of filtering as these could be improved in any existing technique. Also, determining the goodness of a visualization is difficult [31] and requires a subjective study. We then conducted a formal user study to compare Parallel Sets with ICE.

#### 7.1 Initial Comparative Evaluation Using ACH

The Analysis of Competing Hypotheses (ACH) is a technique to choose the best possible solution to satisfy a set of hypotheses. Fitting our overarching application scenario, we only evaluated the existing techniques (and ICE) in terms of the specific task of analyzing a set of categorical data with respect to a numerical target variable. It corresponds to the interaction and technique design stage of the nested model by Munzner et. al [46, 48]. We derived six hypotheses from the requirements listed by the system performance experts (see Section 4) as follows:
Although the ACH evaluation revealed that both Parallel sets and ICE was not supported by any of the existing techniques (only ICE). Table 1 shows the results of the ACH-based evaluation applied to the available visualization techniques and our ICE. The comparison shows that by eliminating any visualization technique which does not satisfy one or more of the hypotheses, only parallel sets and ICE fit all hypotheses.

Table 1. Competing hypotheses analysis on existing visualization techniques and our ICE tool.

<table>
<thead>
<tr>
<th>Hypotheses</th>
<th>Fused Displays</th>
<th>MCA</th>
<th>Parallel Sets</th>
<th>Dimension Reduction</th>
<th>MDS, T-SNE, UMAP, tSNE</th>
<th>Spectral Clustering</th>
<th>Isomap</th>
<th>Scatterplot Matrix</th>
<th>Bisplots</th>
<th>ICE tool</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1: Allow an assessment of the distribution of a numerical variable in terms of a given parameter.</td>
<td>✓</td>
<td>✓</td>
<td>×</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>H2: Allow an assessment of the correlation between parameters.</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>H3: Enable quick filtering.</td>
<td>✓</td>
<td>✓</td>
<td>×</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>H4: Allow an assessment of the statistics alongside the distribution.</td>
<td>✓</td>
<td>✓</td>
<td>×</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>H5: Allow informed predictions.</td>
<td>✓</td>
<td>✓</td>
<td>×</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>H6: Provide insight on aggregate distributions.</td>
<td>✓</td>
<td>✓</td>
<td>×</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

H1: Allow an assessment of the distribution of a numerical variable in terms of a given parameter. The visualization is able to display the distributions of the dependent numerical variable for each parameter. The analyst can get an estimate of the nature of this distribution: bi-modal, multi-modal, uniform, normal distributed, etc.

H2: Allow an assessment of the correlation between parameters. The visualization makes it possible to compare or correlate the parameters in the dataset with respect to their impact on the target numerical variable. Irrespective of the method of correlation, the analyst should be able to derive informative conclusions while filtering the parameter space based on correlation.

H3: Enable quick filtering. Filtering is used to track the best performing configurations for a desired goal. The visualization technique enables the analyst to add, remove and edit the parameters of the configuration and see updated distribution of the dependent numerical variable within one second.

H4: Allow an assessment of the statistics alongside the distribution. The visualization technique displays the statistics (mean, median, percentiles, max, and min) of the dependent numerical variable for each parameter.

H5: Allow informed predictions. The visualization provides cues to the analyst for filtering the parameter space.

H6: Provide insight on aggregate distributions. Similar to requirement R6, the visualization technique provides a summarized display of the dependent numerical variable values which can be reached from a given parameter setting.

7.2 User Study Comparing Parallel Sets and ICE

Although the ACH evaluation revealed that both parallel sets and ICE could be used to analyze categorical variables in the context of a target numerical variable, our computer systems experts voted against the use of Parallel Sets. This was because Parallel sets become too cluttered to effectively filter the parameter space for larger datasets. Nevertheless, to make these informal impressions more concrete, we conducted a user study to compare the effectiveness of ICE and Parallel Sets. The main objective of the user study was to compare the ICE and Parallel Sets based on two metrics: Time to filter configurations and Accuracy of filtering. The participants in the user study were divided into three categories based on their expertise: System performance experts (SE), Visualization experts (VE), and Non experts (NE). SEs were researchers working in the area of system performance, VEs were researchers working in the area of visual analytics, and NEs were users with no research experience in either of the two areas.

A question bank for the user study was compiled with the questions designed by three system researchers (independently), to uniformly represent the requirements of the systems community. After an initial usage tutorial, participants were given two unique sets of five randomly sampled tasks from the question bank to perform on both the tools. The dataset used in the study was the systems performance dataset as described in Section 3. The user study was conducted on 21 users: 7 SE’s, 7 VE’s, and 7 NE’s. Among the total participants, the gender composition was 9 females and 12 males with the overall age range of the participants being 22 to 34 years.

The results of the user study proved the effectiveness of ICE tool over Parallel Sets both in terms of accuracy and time to filter the parameter space. The average time for users to solve a question on ICE tool was 47.6 seconds as compared to Parallel sets which was 73.3 seconds. To compare the statistical significance of time difference, we performed a paired t-test on the distributions of average time to answer a question for each user on both the tools. The p-value of the single tailed t-test was p = .0074 which is lower than the significant value of .05. Hence, the mean time to filter the parameter space is lower in ICE as compared to Parallel Sets with a high probability.

A similar analysis was done to measure the accuracy of each user on the five questions in the user study. The average accuracy of the participants using the ICE tool was 4.37 compared to 2.75 for parallel sets. The p-value obtained on the single tailed t-test for the comparing accuracy distributions was p < .001, which is significantly lower than the threshold of .05. Hence, the mean accuracy of the analyst for parameter filtering via the ICE tool is higher than via the Parallel Sets with a high probability. Given the results of this user study we conclude that ICE is better for multidimensional parameter space analysis both in terms of accuracy and time when compared to Parallel Sets.

We also analyzed the mean accuracy and time based on user expertise. The NEs took the most time for answering the user study questions and had the lowest accuracy as compared to other expertise categories with both of the tools. Also, the VEs were the most accurate with their answers but took a little more time compared to the SEs. However, the trend of expertise-wise accuracy and time is the same for both ICE and Parallel sets. All plots for the expertise wise analysis and the user study tasks along with the dataset are provided in the supplementary material.

7.3 Case Studies

We also evaluated the ICE with case studies derived from two datasets taken from Kaggle.com [1,2]. One dataset is an HR dataset of a US firm containing data on the hourly pay of its employees based on various parameters. The other is a French population characteristics dataset where the population distribution of a set of cities in France is studied at a private firm, and Expert B who evaluated the ICE tool on the French population dataset was an expert survey analyst.

7.3.1 Exploring the HR Dataset

This case study uses the ICE for exploring the HR dataset. The dataset has seven categorical variables: Marital Status, US Residency Status, Hispanic status, Race, Department, Employee Status and Performance Score and one dependent numerical variable: Hourly Pay Rate. To start out, Expert A (EA) first familiarized himself with the dataset and the usage of the ICE tool. Figure 11 has a part of the initial screen he browsed. It shows three of the seven variables with respect to hourly pay scale. Some of the more interesting observations he made were: (1) Married workers had the highest hourly pay and the mean hourly
pay was highest for single workers. (2) The mean hourly pay of non-
residents who are eligible for US citizenship is higher than those of the
residents. (3) White workers have the highest hourly pay among all races. (4) Considering the departments, the executive department had
the highest hourly pay scale followed by IT services.

After the initial analysis, the other two variables in the dataset that
were of particular interest to EA were Employee Source and Perfor-

ing Score. He wanted to see whether high performing employees
were properly compensated for their valuable efforts. The Parameter
Explorer made this investigation easy and EA quickly confirmed that
exceptional employees were indeed paid more than other employees,
with a mean pay of about $40 per hour, shown in Figure 12.

Another parameter of interest was the hiring source of these excep-
tional employees. EA selected the exceptional performance score in
the Parameter Explorer. This filtering updated the Employment Source
group to only show the sources of exceptional workers with respect to
their hourly pay. Figure 12 shows the result of this filtering and the
caption offers a few interesting observations.

EA suggested that for better equality of all sources of exceptional
workers, their mean hourly pay should be similar. Also, EA suggested
that investment on college fairs and job sessions should be lowered as
they are not a good source of exceptional workers. EA then confirmed
that the use of ICE would help the HR department to better manage
the company’s funding and investments.

7.3.2 Exploring the French Population Dataset

The French population habitation dataset has been collected to show
existing equalities and inequalities in France. It consists of four cat-
gerorical variables (City, MOC (Method of Cohabitation), Age group,
and sex). The dependent numerical variable, Population count, is the
number of people in each of the categories defined by permutations of the
independent variables, for example, one category might be adult
females with age 21–40 living in Paris with her children. Expert B (EB)
as a survey analyst and like Expert A he first familiarized himself
with the ICE tool by looking at an overview of the dataset’s variables.
The overview screen of the ICE showing the population distributions,
and statistics is provided in the supplementary material. EB’s initial
observations were: (1) The population count for a few categories in
Paris is exceptionally high compared to other categories because the
mean is very low compared to the highest value. This can also be seen
in Figure 13. (2) The mean population of the age range 60–80 is the
highest in all cities; (3) The age group 20 to 40 is the lowest on average
for all cities; and (4) The average number of females is higher than the
average number of males for the overall population.

Following the basic inferences, EB was further interested to study the
habitation methods of females in three major cities of France: Paris,
Marseille, and Lyon. EB selected Paris from the City variable followed
by 2 from the Gender variable. The Parameter Explorer then showed
the distributions of population for all categories of habitation methods,
as shown in Figure 13. EB could see that the most females were
children living with two parents, i.e., category 11 (shown by a single
dot because all of these females have the same age group of below 20
years) followed by females living alone (i.e., category 32). Similar
analyses were done for the cities of Marseille and Lyon. For Marseille,
EB pointed out that almost an equal number of females lived as a single
household and in a family with children. For Lyon, most females were
the children living with two parents followed by females living as a
single household. EB then used the Provenance Terminal to go back
two stages in the filtering process to compare the female habitation
in all cities. EB further pointed out that Paris had exceptionally large
number of children living with single parent as compared to other cities.

After evaluating the use of the ICE on the France population dataset,
EB recommended ICE as an effective tool for the quick filtering and
understanding of survey statistics. EB also found the ICE tool helpful
in understanding biases in the population distributions.

8 Conclusions

This paper presents the ICE tool, a novel approach for categorical pa-
rameter space visualization in the context of a dependent numerical variable.
ICE overcomes the existing challenges by providing an effective layout
for parameter space visualization. The stacked R-D bars concept used
in ICE along with interaction assists in effective filtering of the param-
eter space. A greater number of parameters could be visualized and
readily correlated, thus increasing the efficiency of filtering. Multiple
configurations can be compared for their impact on the target variable
based on any objective. ICE also supports multi-objective filtering
since it presents full statistics and distribution information to the user
for each parameter level.

Several important lessons were learned while designing the idea of
ICE. In the requirement analysis phase with the systems community
researchers, we realized that by presenting the results gathered from
the dataset with existing visualization techniques helped make the
gathering of requirements more effective. Almost from the start, the system experts were skeptical about the accuracy of most existing techniques. They wanted a tool that would be able to show the statistical distributions precisely. It also helps to keep a keen eye on any struggles the collaborating domain experts may experience. For example, in the filtering experiments we noticed that they had trouble remembering the filtering path. This gave rise to the provenance terminal.

Besides the effective design of ICE, there still remain some limitations which can be taken up as the future work. For larger datasets, techniques to combine multiple parameters can be incorporated to prevent excessive thinning of the bars. Moreover, some related precomputed solutions can be provided to the analyst based on optimization objectives to start off with the search process. Also, ICE is based on the assumption that the cost of changing parameters is the same throughout, which might not be true in some cases. Moreover, these costs might vary with time. It will be useful to incorporate cost measures into ICE and provide support for real time cost based filtering. We will continue working on our ICE tool to incorporate these new features.

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Workshop: Beyond Time and Errors—Novel Evaluation Methods for Visualisation

International Conference on Discovery Science

Information Visualization Symposium

and computer graphics


