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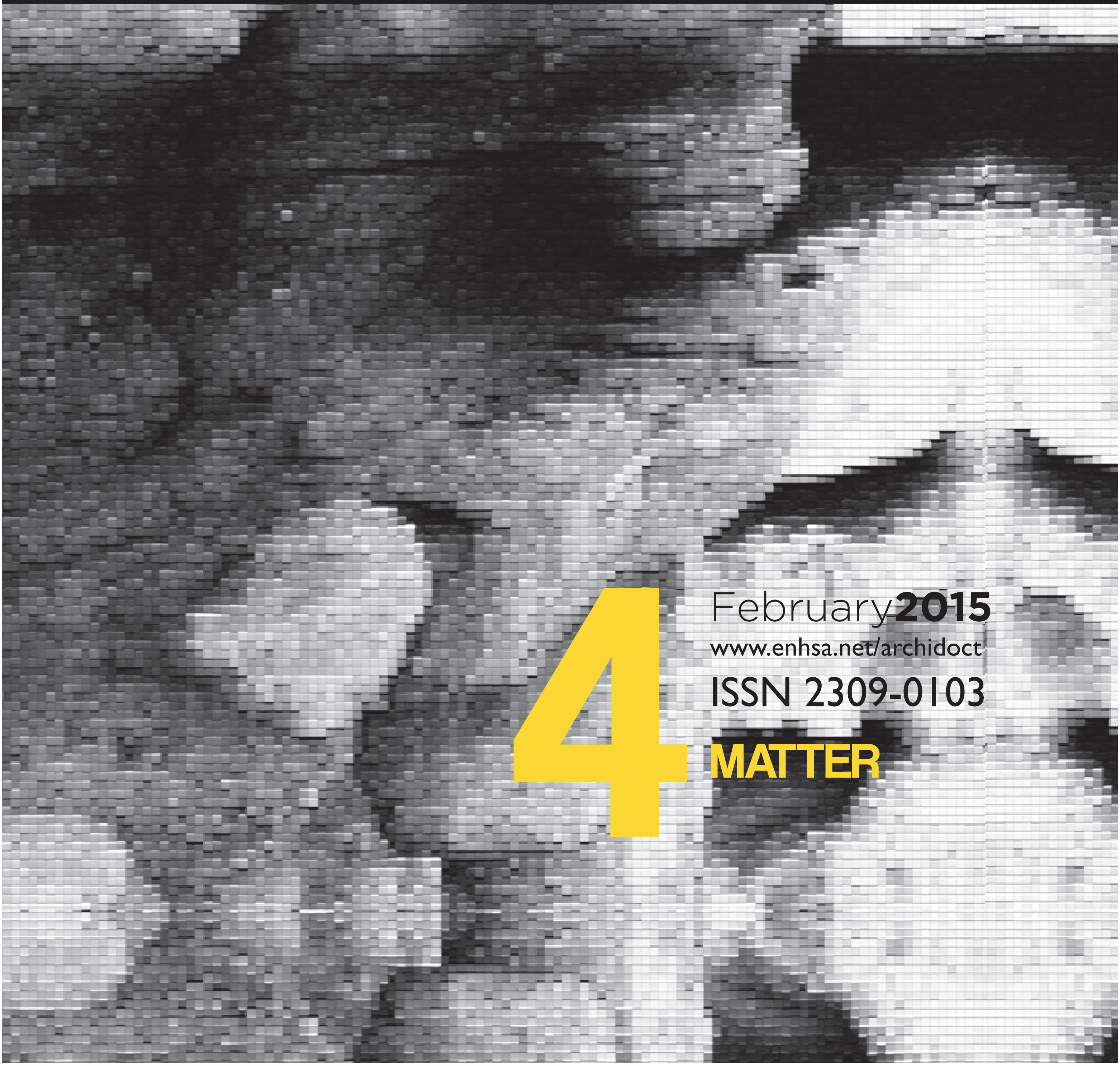

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Propositional architecture and the paradox of prediction

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Abstract

If Architects had a tool to predict future demands, modification of the built environment could meet the changing behaviors and emerging phenomena in society. Research on existing building stock, in relation to prediction is reviewed. And an entirely new type of architectural tool is proposed.
The algorithm, capable of making predictions in unstructured environments, is presented, and the basis and the idea of the algorithm are described. The discussion focuses on possible applications for this new tool, and the paradox of prediction is debated. Finally, improvements to the computational system are proposed.

Keywords

Building Stock; Prediction; Forecasting; Build Environment; Algorithm; Computation.

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1. Introduction

What if we could predict trends, rising phenomena and future necessity in our built environment? What if we could trace behaviors and forecast the needs for the future? What if we had a tool for proposing architecture, able to point out potentialities and suggest additions, subtractions and modifications?

Our societies nowadays change faster than ever, and as both long term and short term demands change, our physical surroundings need to adapt in a rate where real-time feedback is too slow for the time-consuming process of building. There are few ways to react to this issue. One is to make use of the existing building mass and only focus on the smallest most time-utility effective modifications. The other is to start modifying before the need actually arises; a preemptive strategy, which requires prediction. Prediction easily becomes either a technical engineering issue or a philosophical issue. This changes with the grade of fuzziness versus determinism of what we must predict. The article does not discuss the philosophical aspects of prediction, rather assume prediction from a cognitive viewpoint, where experience creates the basis of forecasting - through the ability to remember similar situations and project their continuation.

As society, culture and especially demographic setting change, many aspects of the architecture should follow. As an example, families get smaller, more people live alone in the same size apartments as 50 years ago, and density drops causing change in the urban scale. Drop in density makes it harder to run efficient public transport, and small-scale local shopping demise. If the existing housing mass would continuously adapt to the need, mixed use could nurture social integration, less transportation, and lower general consumption. Much of this adjustment could be achieved through subdivision infill buildings or merging of existing property (Anne Power, 2008). In addition, enormous amounts of industrial spaces have been left empty as the situation for industry in Europe has changed over the last 35 year, however reliable data are missing in order to form coherent refurbishment plans, and in addition it is not high on the agenda of the architecture community, as architectural education, by and large, focuses on (new) building designs (Hassler, 2010).

If we are able to predict phenomena for large-scale environments, the proposals for modification could be anything from subdivision of living spaces, opening of ground floors, addition of balconies, infill houses, or demolitions to create parks, and urban spaces. Basically including all scales of modification to the built environment, through both subtraction, addition, and modification. The importance lies in being able to propose modifications, in the rate of which the demand changes.

Figure 1.
This simple robust structure from 1924 was serving initially as garage, but has since been modified to fit several different needs. Through the 80s and the 90s the building has served as a shop for outdoor apparel. (Brandt, 1994)

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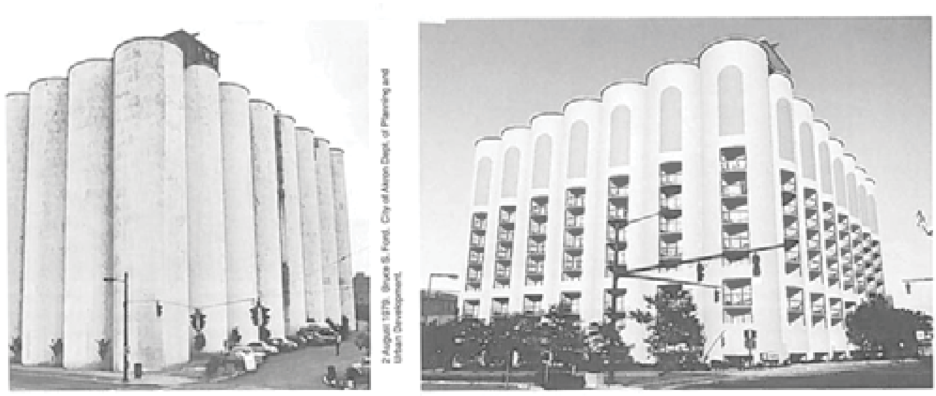

Figure 2.
As the downtown Akron, Ohio, grew closer to the grain silos of the Quaker Oats Company, it was decided to transform the structures into a hotel, now known as the Quaker Hilton. (Brandt, 1994)

2.1 Related work on prediction used on the existing built environment

Kohler and Hassler sums up the research on refurbishment and the building stock, and describe the different strands. In addition, I will mention some research done by engineers. One area is the energy refurbishment research, where buildings are divided into groups based on various parameters such as annual consumption, surface area, age, function and inhabitants, with the aim to make overall predictions of energy consumption for coming years. Hassler comments on these models, saying that rather than predicting the results of refurbishment, the need is to form a strategy for future refurbishment (Hassler, 2010).
Research by Stepney that looks more general, and includes social, environmental, and cultural consequences of demolition in comparison to refurbishment, without actually doing a prediction, highlights a complex landscape of causal effects - ranging from local through political, social and global consequences. She concludes:

"It is unclear how energy use will work out in practice. So, an approach grounded in the realities of our complex built environment seems more hopeful than a theoretical, long-term and largely uncosted plan to build and demolish on unprecedented scales within our seriously constrained environment."

(Stepney, 2008)

Another strand is the traditional research in conservation that focuses on conservation of historically significant buildings. This refers - depending on country or region- to as little as 1-2% of the building stock (Hassler, 2010) and one of the discussions in this field is to what extent the original functions of the building should be maintained in opposition to suggesting and refurbishing for new functions and possible uses.
Kaklauskas and his colleagues make a full multi-criteria analysis, where all criteria like cost, aesthetics comfort and quality are quantified in tables. They are basing the system on set of weighted criteria, which would probably change weight or value depending on the environment in which the refurbishment is taking place (Kaklauskas, 2004).
Yet other research into prediction of the building stock development, has focused on energy consumption and uses production statistics and implicit trend models to predict the future behavior of the stock. Those studies look at average trend curves from the entire environment, in single separate dimensions and project many years into the future, with

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large margins (IEA, 1995).
However, sustainability, heritage and refurbishment have both to do with the past and the future of our built environment. While architectural heritage is concerned with sustaining culturally valuable buildings for the future, refurbishment is about adapting the built environment to future needs of its inhabitants, so that new sets of demands can be met. But, how do we determine what the demands are, and what attributes of heritage we should attempt to keep? Do we keep cultural values and resources through conservation, preservation or protection? Maybe it is done through maintaining utility and nurturing active use of our built environment. An approach could be to use existing potentials in combination with future trends, occurrences and phenomena.
If that is the case, attention is no longer on the design and formal expression and aesthetics of the physical matter in the environment. Rather, the subject can be seen as constituted by the events and occurrences in the environment. A matter composed by events, activities and episodes.
"An episode is a collection of events that occur relatively close to each other in a given partial order."
(Manilla, 1997)
Events make up episodes, which are perceived less through conventional spatial metrics and categories, more through our human sensorial apparatus and cognitive sense making. Episodes are often considered to pass over time, but when understanding them as series of events, time is not preconditioned, it may or may not be regarded.
The article seeks to understand the paradoxical consequence of using prediction in architecture and speculates on ways of implementing prediction as a tool for proposing modifications to our built environment. The chosen research approach, is referred to as Propositional Architecture and is described in the paper "Propositional Architecture using Induced Representation"(Nielsen and Dancu, 2014). It uses sensor technology, cognition, and augmentation combined, in order to achieve an ongoing stepless refurbishment of the existing building mass. The approach consists of a few steps. A: data collection from the environment, B: machine cognition, learning, prediction, and, C: proposition, visualization, and embodied representations for quick implementation. The paper outlines the factual and theoretical basis for this approach, and discusses three experiments, each one of which deals with steps A, B and C.

2.2 Machines understanding events

Already in the 90s, when sensor technology was recognized as one of the important emerging technologies, the ability to process sensor data in software became an important area of development (Toko 2000, Laughlin 2002, Murphy 1996). Nowadays sensors are heavily enhanced by more advanced software methods such as 'Sequential Pattern Mining' and 'K-means clustering', Self Organizing Maps, and others (Gershman, 2012, Cabanes, 2010). The combination of these different types of algorithms, can result in systems performing machine learning and cognitive processes. Systems that can reveal hidden relations in large unstructured data, learn to recognize consumer patterns, objects in images, handwriting, or faces.
Through using different algorithms in combination, this (accumulate) algorithm can propose the occurrence of future phenomena, provided that it has an amount of experience. That means that the algorithm can be assigned to a higher level than analytical machines or design machines, namely that of initiative and proposition. The algorithm permits the identification of behaviors and thus it is able to propose what is necessary in the future. The ac-

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cumulate algorithm might permit us to build and modify for future events and phenomena.

2.3 A new type of computational aid for architecture and the built environment

Machines throughout the past century have increasingly managed design; perspective perception apparatus for hand drawing and parallel drawing machines for geometrically constructed perspectives. In the last few decades, computer aided design machines have evolved, and the late twenty years computerized parametric machines have come about. The parametric machines allow architects to manage complex geometry, data and relations, and some simulation models already simulate notions of events and occurrences in the environments they model. Such technologies enable architects on a level of design and development of ideas that are already conceived.
If we change the focus from handling geometry to the task of handling behaviors and events in matter, maybe we can use computational and sensory machines for the very conception of ideas. The computation and technology in this research is not for the design of existing ideas, rather aiding in the very conception of ideas. Propositional Architecture could point out potentialities in the environment and suggest modifications.
A learning algorithm is proposed that is able to detect phenomena and make predictions on events in any given environment, real-time. The algorithm can be fed any input data, in any number of dimensions, and the algorithm can easily adapt to any timescale.
The algorithm searches its memory and when pointing to a part of the memory, it indicates that there is a certain phenomenal similarity between the current and past experiences. Representation of the projected memory can be in any form of medium, but this is the prediction.
These are the steps which is performed in continuous repetition:

A: Collect and memorize multiple types of data from the environment.
B: Produce an internal representation of events and phenomena. (This representation constantly shifts depending on the character of the data.)
C: Compare the current series of events to all previous series of events and find behavioral similarities, and recurrent phenomena.
D: The forecast takes the ‘soon to come’ events from the most similar previous phenomena, and projects it into the future.

3 Forecasting method

Most of the simple forecasting methods are based on running averages, linear regression, trends, or curve-fitting models, all included in linear prediction. Non-linear prediction is also rich presented as frequency identification or Fourier transform analysis for more complex curves (Antunes, 2001) or statistical methods using, for example, the Bayesian theorem (Gershman, 2012). Also neural networks have been used (Dorffner, 1996), but these methods suffer from the problem of long training time.
The algorithm presented in this article can be placed within the group of ‘Advanced time-series forecasting methods’, and the most similar approach can be found in the article ‘Rule discovery from time series’ (Das, 1998).
In this case, where the changing factors are spatially distributed and it is in fact not clear what exactly we need to forecast, this work takes an approach favoring robustness and speed, while still being able to have a real-time graphic representation.

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If we assume for a moment, that all events and phenomena are constituents of other smaller or larger events, then if a certain sequence of partial events takes place, we should be able to remember it and project the next few parts of that event, provided that we have experienced a similar series of events before. This means that we need a system, which can separate the occurrences in the environment into different partial events, and then compare the current sequence of partial events to all the similar sequence of partial events in memory. Laplace describes determinism like in the quote below, but he assumes that we must know, through science, all meaning of the individual parts in the entire universe, but we may just need to look for similarities to previous occurrences, without knowing the meaning of the events.

"We ought to regard the present state of the universe as the effect of its antecedent state and as the cause of the state that is to follow. An intelligence knowing all the forces acting in nature at a given instant, as well as the momentary positions of all things in the universe, would be able to comprehend in one single formula the motions of the largest bodies as well as the lightest atoms in the world, provided that its intellect were sufficiently powerful to subject all data to analysis; to it nothing would be uncertain, the future as well as the past would be present to its eyes. The perfection that the human mind has been able to give to astronomy affords but a feeble outline of such an intelligence."

(Laplace, 1820)

The idea of the algorithm is that, if several aspects of the environment are observed throughout a period of time, a memory of the events taking place is built, and if the most recent series of events is found to be similar to a previous series of events, then we may presume that the continuation of the current situation is similar to the continuation of the event from the memory, so that it becomes the prediction.

3.1 Experience built from multidimensional data

One sensor can support many simple tasks, but for the data to be usable, it must be both calibrated and context aware. Through the technique of sensor chaining, multiple same type sensors can perform without calibration, only with context awareness. Instead of calibration they make use of their different readings set in relation to their different contexts. Context awareness, high precision and adequate reaction speed are required of sensors used for sensor chaining (Nielsen, 2012). Sensor Fusion, on the other hand can significantly reduce the need for both precision and context awareness for the individual sensors, as this technique makes use of various criteria, or what we will refer to as 'dimensions'.

If you cannot find the sensor you need in any manufacturer´s catalogue then you can probably make your own - in Software. This is the basic premise behind sensor fusion. The idea is that if you combine the data from a variety of different sensors, you will be able to measure parameters for which no single sensor exists" (Laughlin, 2002)

With sensor fusion systems, a rough calibration is useful, and this is how we might understand the system described in this paper. This algorithm can be seen as a sensor-fusion system, using sensor chaining throughout time. We look at each unit of time as a multidimensional data point, and compare its values to all other time units in order to determine which are similar and which are different. We employ a simple K-means clustering algorithm to determine the differences throughout the time-data points. This is the basis for creating a sequence.

The K-means algorithm, commonly used for signal processing, is clustering the n-dimensional observations into any given number of clusters, where similar observations are grouped together. If we had two-dimensional observations plotted on paper, we could

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divide them in two different clusters. Then we could calculate the average centerpoint for each cluster, and then find out for each point which centerpoint it is closest to. Then recalculate a new position of each centerpoint based on the average of the points belonging to the cluster with that centerpoint.
Increasing the number of clusters could still be visualized, but when we increase the number of dimensions for the data points, we can no longer visualize them after 3-dimensions. However the K-means algorithm uses the same approach, calculating the distance over n-dimensions, and comparing the Euclidean distance between clusters and data points to tell if the point belongs to one or the other cluster, even for a very large number of dimensions.
When looking at the time-data-points in the order which they are recorded, a sequence can be derived where each new element is given the name of the cluster to which the time-data-points belong and a length which is determined by the number of consecutive time-data-points belonging to that same cluster (Figure 3). We call one such element 'subsequence'. This method is a strong discretization of the data, but by continuously redistributing members of the clusters, it is constantly reinterpreting its understanding of the data in accordance with the latest experiences. So if no particular phenomena take place, -say all sensor input has only minor changes, the distribution will still occur. One might say it adapts to the degree of complexity in the environment.
The last step is to look through that sequence and find a series of subsequences similar to the most recent series of subsequences, -the 'now'. Once a good match is found from the previous event sequence, we can look at how that earlier event unraveled and propose that same course of events to pass again. A similar approach is described and used here (Das, 1998). For this purpose I made an algorithm performing '*recursive temporal data mining*'.

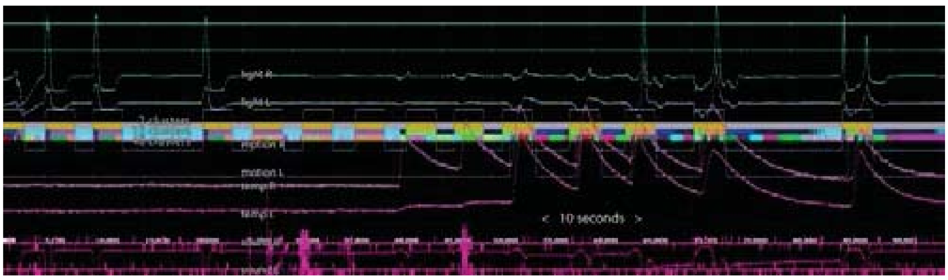

Figure 3.
Sensor readings are plotted over the duration of about 100 seconds. The data is analyzed, and vertical time sections with similar sensor readings are clustered. The result is shown as the poly-colored bar across the middle. Same color time sections have similar sensor readings.

3.2 Temporal Data Mining

Temporal data mining is a widely applicable field, and most real world data can be viewed as sequences of events, which can be used as input for temporal data mining. This algorithm makes use of recursion to find the best matching previous event. As the bottom part of figure 4 indicates, the recursion starts once for every previous subsequence with the same name (or color). In order to investigate the similarity between the current sequence and the sequence back in the memory, one step backwards in both sequences is made, and if the subsequence has the same name, the recursion is called again. By summing up the lengths of sub sequences and giving penalty when the length of the sub sequence pieces

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mismatch in length, the longest, matching sequence can be found.
As already mentioned, there are literally hundreds of different algorithms published within the field of data mining, rule mining and sequential data mining. They are mainly different in optimizing speed for searching large data sets, which is in part because the task of finding any sequence with any length, and any number of its occurrences, is a task that increases exponentially in size with the increase in data. Often the algorithms need to be appointed a size of window, from which the sequences can be mined, and a criterion of support may also be defined. The window separates the task in smaller chunks, and the support defines how much to look for patterns (Fournier-Viger, 2014).
Because this algorithm only searches through memory in relation to the latest sequence, and because it uses recursion, the mining takes just few milliseconds. Additionally, for the recursion to be robust to noise in the sequence, that is built in a criterion of noise tolerance. It works like a jump with penalty. If the next sequence piece does not match, the second is queried, if that also doesn't match the third is queried. This maximum number of jumps is a variable, a noise tolerance. And the penalty is deducted from the sequence length index, which determines what sequence is chosen for the forecast.

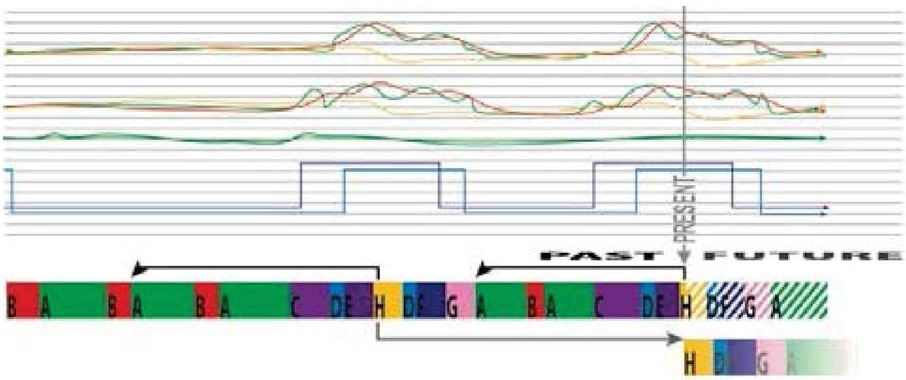

Figure 4.
Top; The input dimensions of various data assigned to each time-data-point. Bottom; Recursive temporal data mining, and the projected sequence making the prediction: HDFGAB.

3.3. Pseudocode:

1. Add new data point to memory - assigned with incoming data dimensions
2. Reorganize cluster names for data points using k-means clustering
3. Write whole sequence of subsequences using cluster names from k-means
4. Start recursion for each previous subsequence equal to the current subsequence -return the longest matching sequence
5. Forecast from the end of returned sequence
6. Continue until better sequence is found
7. If memory is full, start overwriting oldest memory
8. Repeat from 1.

4. Example of use

The algorithm was tested on an outdoor area of ETH, campus Hönggerberg. The area is providing access for pedestrians between the campus buildings and the busses, connecting

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the campus to the city. The input dimensions are, in this case, given the color of the pixels indicated by grey squares in figures 5 and 6, and the memory was recording a span of about 5 minutes, before starting to overwrite old memory. The prediction is illustrated as a series of green traces showing what pixels are going to change in comparison to the normal image. Figure 5 is not a real prediction because the algorithm was shown the same exact video twice, but it demonstrates how the algorithm shows the most similar previous series of events, namely the exact same previous events. Figure 6, on the other hand, was shown a continuous video of all events in the area, and although it is obviously not able to predict the situation, it is able to find a series of similar events, where several of the pedestrians are seen in the same areas simultaneously.

This is obviously a very difficult situation to predict because the environment has little or no causal behavior, and almost none of the events are related, but rather spontaneous and chaotic.

Figure 5.
Testing and demonstrating the capacity to predict. The algorithm was shown the video twice, and the second time it was able to use the first as prediction. Prediction is displayed in green.

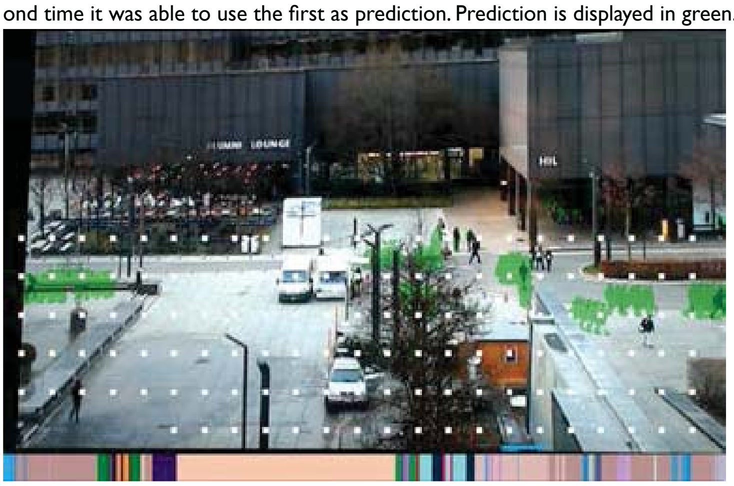

Figure 6.
The algorithm is shown a long video, and the chosen moment is when the algorithm finds a similar series of events. Prediction is displayed in green.

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5.1 Paradox of prediction

How do we verify a prediction if we intentionally change the environment in which it were to play out? And should the prediction be created from memory of modification based on prediction?

The questions suggest two different ways of using the algorithm, one where the memory is based on past cases of refurbishment, it would, given the data from a vast amount of other cases, be able to suggest the most similar outcome, and provide data on more aspects such as built time, cost and other detailed data from the past case(s); for example, if memory was made up of a number of refurbishments in different locations, where each was tracked over time with essential criteria. Then when another refurbishment is started, the most similar can be found and predictions can be based on that previous refurbishment. Of course as the refurbishment progresses, the prediction would change, as other better fits might be found. That way future potentials might be seen earlier and exploited better.

The alternative is without using past refurbishment as memory, instead using occurrences of events and trends in the environment, in order to produce designs that support the events. This could, for example, be shifts in functions of a certain area. In case we have multiple dimensional data over time with information about how inhabitants and industry behave in the city, then recurring events of movement to a new part of the city can create the sequential memory. The algorithm will be able to make a prediction of which inhabitants are likely to move within a given time.

If input dimensions are imperceptible, might we predict on imperceptible phenomena?

If we make use of dimensions imperceptible to humans, we might identify series of events that are otherwise imperceptible. What Immanuel Kant describes as noumenon. Predicting may work the same or better, it needs to be experimented with (Rescher, 1972).

How can we provoke reactions for faster learning of relevant phenomena?

An example is the unfamiliar water faucet, one might not know what happens when it is turned versus levered. The approach to learn is to affect it. In this way, after a few operations, it is learnt which operation supplies water pressure and which operation regulates temperature, but gaining this experience, is impossible through just passively observing the faucet.

Interplaying with the environment might increase the rate of which learning information, sufficient for prediction, can be gained. But this points back to the first question in this discussion.

5.2. Improvements to the forecasting method

How could we improve the choice of sequence?

One of the most important aspects of the prediction is to choose the sequence to use for prediction, and it is obviously already dependent on the differentiation of time data points and the granularity of the sequence. The approach of finding the longest possible set seems like a reasonable strategy for the very diverse forecasting environment.

How might we improve the input dimensions?

Another very important criterion is to choose relevant input dimensions. These should be related to the situation relevant to the prediction. Essentially according to the idea of fusion sensors, improving the number of different sensorial aspects improves the robustness. Dimensions for which nothing happens will be non-influential, and only dimensions with no

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causal relation to the situation of relevance can be creating noise. It would be relevant to construct learning filters which are able to 'sharpen the senses', thus reducing the influence of noise dimensions.
Such filters might be constructed through supporting the dimensions, which are active when recurring sequences are found, and inhibiting the dimensions that are inactive when recurring sequences are found.

Can we use Induced Representations as input dimensions?

The more qualitative the input can get the better, so if we were to supply the prediction algorithm with pre-analyzed data e.i. representations, as opposed to raw sensor data, the algorithm might perform well on different environments in parallel. For example city parts may be compared and occurrences from one city part can be used as memory for another.

6. Conclusion

The article presents an approach to architecture where, instead of the conventional architecture design approach, a tool for proposition of new interventions is presented; a shift from designing existing ideas towards that of proposing new ideas for intervention.
An algorithm which, provided multiple dimensional data, can make predictions of events and phenomena in highly fluctuating and diverse environments, and if applied correctly, it can identify and propose new ideas for interventions.
The algorithm is presented and described in detail. Possible unexplored applications for the algorithm as well as improvements are discussed and in the future research, aspects such as multiple layers of memory, as well as partial predictions should be explored. There seems to be both vast applications for prediction, as well as many opportunities for using the concept of Propositional Architecture.

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In the entire year 2014 I have been Guest Researcher at Prof. Ludger Hovestadt, Chair for Computer Aided Architectural Design, Department for Architecture, ETH Zürich. Here the research took another turn into a deeper understanding of advanced computation. I would like to thank Prof. Ludger Hovestadt for opening a more versatile approach to computation, and Vera Buhlmann for a general understanding. I will also mention Atli Seelow for his help improving the chapter on related work, and my supervisor Monica Billger for advice. The project is funded by the project Architecture in the Making and Chalmers Technical University Department of Architecture.

References

Antunes, Cláudia M., and Arlindo L. Oliveira. (2001) "Temporal data mining: An overview." KDD Workshop on Temporal Data Mining.

Zhang, Zhiqiang, and Qiong Zhu.(2013) "Fuzzy Time Series Forecasting Based On K-Means Clustering." Open Journal of Applied Sciences 2: 100.

ISSN 2309-0103
www.enhsa.net/archidoct
Vol. 2 (2) / February 2015

Mooney, Carl H., and John F. Roddick. (2013) "Sequential pattern mining--approaches and algorithms." ACM Computing Surveys (CSUR) 45.2.19.

Guenael Cabanes and Younes Bennani (2010). Learning the Number of Clusters in Self Organizing Map, Self Organizing Maps, George K Matsopoulos (Ed.),ISBN: 978-953-307-074-2

Gershman, Samuel J., and David M. Blei. (2012) "A tutorial on Bayesian nonparametric models." Journal of Mathematical Psychology 56.1: 1-12.

Laughlin, C., (2002) "Sensor Fusion + New Materials", editorial, Sensor Review vol 22#4 Emerals Group Publ. Ltd

Guenael Cabanes and Younes Bennani (2010). Learning the Number of Clusters in Self Organizing Map, Self Organizing Maps, George K Matsopoulos (Ed.),ISBN: 978-953-307-074-2

Manilla, H.(1997) "Discovery of Frequent Episodes in Event Sequences" Data Mining and Knowledge Discovery 1, 259–289

Toko, K., (2000) "Biomimetic Sensor Technologies" Cambridge Press

Laughlin, C., (2002) "Sensor Fusion + New Materials", p.7-editorial, Sensor Review vol 22#4 Emerals Group Publ. Ltd

Murphy, Robin R.(1996) "Biological and cognitive foundations of intelligent sensor fusion." Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on 26.1: 42-51.

Fournier-Viger, P., Gomariz, Gueniche,T., A., Soltani,A., Wu., C., Tseng,V. (2014). SPMF: a Java Open-Source Pattern Mining Library. Journal of Machine Learning Research (JMLR), 15: 3389-3393.

G. Das, K.-I. Lin, H. Mannila, G. Renganathan, and P. Smyth. (1998) Rule discovery from time series. In Proceedings of the 3rd International Conference on Knowledge Discovery and Data Mining.

Dorffner, Georg. (1996) "Neural networks for time series processing." Neural Network World..

Brand, Stewart. (1995) How buildings learn: What happens after they're built. Penguin.

Rescher, Nicholas. (1972) "Noumenal causality." Proceedings of the Third International Kant Congress. Springer Netherlands.

Kaklauskas, Arturas, Edmundas Kazimieras Zavadskas, and Saulius Raslanas. (2005) "Multivariant design and multiple criteria analysis of building refurbishments."Energy and Buildings 37.4 : 361-372.

Power, Anne. (2008)"Does demolition or refurbishment of old and inefficient homes help to increase our environmental, social and economic viability?." Energy Policy 36.12 : 4487-4501.

IEA (1995) International Energy Agency: Future Buildings Forum. 2nd FBF Think

ISSN 2309-0103
www.enhsa.net/archidoct
Vol. 2 (2) / February 2015

Tank Workshop, IEA, Paris.

Niklaus Kohler & Uta Hassler (2002) The building stock as a research object, Building Research & Information, 30:4, 226-236, DOI: 10.1080/09613210110102238